MEASUREMENT OF TRANSIT NETWORK ACCESSIBILITY BASED ON ACCESS STOP CHOICE BEHAVIOUR

Ali Malekzadeh

Submitted in fulfilment of the requirements for the degree of
Doctor of Philosophy

School of Civil Engineering & Built Environment

Science and Engineering Faculty

Queensland University of Technology

October 2015

Keywords

Discrete Choice Modelling, Logit Logsum, Nested Logit model (NL), Path Size Logit model (PSL), Policy Analysis Application, Transit Access Stop Choice, Transit Network Accessibility, Travellers' Behaviour Analysis, Travellers' Subjectivity.

Abstract

In recent years, increasing traffic congestion and pollution in cities have become a serious risk to the liveability of urban areas and their development. These facts have led transport planners to introduce the concept of accessibility, particularly transit accessibility, in contrast to the traditional mobility approaches. Transit accessibility can be defined as an evaluation of the transit system for reaching to opportunities from the users' point of view and it is an important direction that has recently attracted much attention in current research. However, developing an accurate transit accessibility model is challenging due to the inherent complexities of public transport.

To manage these complexities, a large body of research in the context of transit network accessibility has used simple distance or travel time to estimate transit accessibility to destinations. Some research has also focused on utility-based transit accessibility measures that consider users' behaviour. These existing utility-based approaches to transit accessibility can be improved in possible directions: 1) to effectively capture important attributes (e.g. travellers' behaviour, transit network characteristics) that affect the utility of travel in time-dependent and complex transit networks; 2) to capture the effect of transit route and mode diversities in the network; and 3) to consider the subjectivity of the perceptions of transit network among travellers.

This research developed an access stop choice model to measure transit network accessibility from origin to destination. The discrete choice model in this research was developed as a hybrid model with a nested logit formulation at the mode level and a corrected logit formulation at the stop level. The access stop choice model was estimated using household travel survey data from the greater Brisbane metropolitan region (Southeast Queensland, SEQ) in Australia; the accessibility estimation was also performed and tested in the regional SEQ network.

Modelling the choice model at the stop level not only addresses the problem with accurate prediction of path choices in high frequency transit networks but also captures travellers' access stop choice behaviour and making the combination of alternatives possible. The hybrid structure of the model also rectified two limitations with the

transit choice models. Firstly, the model proposed a nested structure to treat the correlation among the choices of transit modes (e.g. train, bus and ferry). Secondly, the model proposed a correction attribute to rectify the correlation of the error terms among the stop choices, due to route commonalities among the stops. The developed model can apply to passenger's behaviour analysis in transit networks, transit network modelling research and transport planning studies. Other possible applications of this measure are for decision making in evaluating the value of different transit projects in the planning stage and for identifying optimum policies for improving the transit accessibility.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

ASAI: Actual Stop Accessibility Indices

ASGS: Australian Statistical Geography Standard

BIOGEME: BIerlaire Optimization toolbox for GEV Model Estimation

BSD: Brisbane Statistical Division

CBD: Central Business District

CNL: Cross Nested Logit

DTMR: Department of Transport and Main Roads

FTGIS: Florida Transit Geographic Information System

GEV: Generalized Extreme Value

GIS: Geographic Information System

GTFS: General Transit Feed Specification

HTS: Household Travel Survey

ETAI: Environmental Transit Accessibility Index

IIA: Independence of Irrelevant Alternatives

ISAI: Ideal Stop Accessibility Indices

LUPTAI: Land Use and Public Transport Accessibility Index

MNL: Multinominal Logit Model

MNP: Multinomial Probit

NL: Nested Logit

PCL: Paired Combinatorial Logit

PSCL: Path Size Correction Logit

PSL: Path-Size Logit

PSPA: Path Size Penalty Algorithm

PTAL: Public Transport Accessibility Levels

PTWAI: Public Transit and Walking Accessibility Index

RUM: Random Utility Model

SCRI: Stop Coverage Ratio Index

SEQ: Southeast Queensland

SLA: Statistical Local Area

TBSP: Trip-Based Shortest Path

VOT: Value of Time

Publication from this research

Malekzadeh, A., Chung, E., Nassir, N. (2015). Investigating on the transit users' subjectivity in perception of transit network. *Canadian Journal of Transportation* (forthcoming).

Malekzadeh, A., Chung, E., Nassir, N. (2015). Applications of utility-based transit accessibility measure in planning and policy making. *Journal of Transport Geography* (forthcoming).

Malekzadeh, A., Chung, E., Nassir, N. (2015). A behavioural modelling for measuring the network transport accessibility. *State of Australian Cities National Conference, Gold Coast, Australia* (accepted).

Nassir, N., Hickman, M., Malekzadeh, A., & Irannezhad, E. (2015). Modelling Transit Access Stop Choices. In *Transportation Research Board 94th Annual Meeting.*

Nassir, N., Hickman, M., Malekzadeh, A., & Irannezhad, E. (2015). A Utility-Based Travel Impedance Measure for Public Transit Network Accessibility, *Transportation Research Part A: Policy and Practice* (in press).

Malakzadeh, A., Yigitcanlar, T., Bunker, J. M., & Dur, F. (2010). Evaluation of accessibility for knowledge-based cities. *Proceedings of the 3rd Knowledge Cities World Summit: From Theory to Practice*, 696-711.

Statement of Original Authorship

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

Signature: QUT Verified Signature

Date: October 2015

Acknowledgements

First and foremost I would like to express my special appreciation to my principal supervisors, Professor Edward Chung, for his invaluable guidance, support and encouragement throughout my studies. I would like also to express my sincere respect for his care and supervision of my PhD life.

I would like also to express my most sincere thanks to my associate supervisors, Dr Neema Nassir, Dr Tan Yigitcanlar, and Dr Jonathan Bunker for their support and instructive feedbacks to my research.

My appreciation and gratitude extends to the people that have supported me during the research including Dr Brian Lee, Elnaz Irannezhad, Daniel Ng, Dr Hang Jin, Dr Marc Miska and Sarah Carr. I am also so grateful to Jennifer Beale for editing this dissertation.

A special thanks to my family to whom I owe a lot. Words cannot express how indebted I am to my parents for all of the sacrifices that they have made on my behalf.

Finally, I would like to express my deepest appreciation to my wife for her patience, support and consistent encouragement during this research.

Chapter 1: Introduction

A metropolitan area’s economic and social health is entirely related to the performance of its transportation system (Meyer & Miller, 2001). Although it is acknowledged that transport has significant benefits on the growth and development of cities, in contrast, high traffic growth also has significant negative impacts on the environment and economy of cities through traffic congestion and air pollution. During the last few decades, faith in the popularity of growth in mobility and transport has begun to diminish (Gilbert & Tanguay, 2000). Cities across the globe have experienced rapid development during the last five decades and the travel time between residential area and activities is increasing accordingly. These rapid developments typically lead citizens to more automobile dependency, which results in increasing traffic congestion and air pollution in the cities (Banister, 2009; Iacono, Krizek, & El-Geneidy, 2010).

This increased congestion in cities has challenged the belief that increasing travel demand will be satisfied by more motorways. People and policy makers understood that current strategies and development not only reduce the freedom of movement, making the city areas more inaccessible for the inhabitants, but also eliminate the city centres and increase the environmental problems. In addition, they acknowledged that current policies that focusing on the automobile and mobility cannot provide equal opportunities for all residents to participate in different activities, which is the one of the main goals of the transport planning (Greene & Wegener, 1997).

These facts have led transport planners and decision makers to a fundamental change in ways of planning and evaluating the transport system; this change is to introduce the concept of accessibility.

In this chapter the research background (1.1), context of the research (1.2) and the main purposes of this research (1.3) are presented. Section (1.4) is a brief outcome of the significance and scope of work. The final section (1.5) covers the outline of the whole thesis.

1.1.BACKGROUND

In recent years, increasing traffic congestion and pollution in cities has become a serious risk to the liveability of the urban areas and their development. On the other hand, investment in transport infrastructures for improving the mobility could not respond to citizen requirements: it could not bring them ease of access, instead, raising the traffic congestion and reducing their freedom to participate in different activities.

In order to overcome these transport and environmental issues, investing in the public transit is becoming a more acceptable alternative due to its greater use by a wider socioeconomic range of people and its environmental acceptance (Tribby & Zandbergen, 2012). However, evaluating the public transport planning revealed that public transport is not necessarily an effective solution if it cannot provide ease of access to all residents.

This fact leads transport planners to introduce the concept of accessibility, in contrast to the traditional mobility approaches to transit planning.

In general, accessibility shows the ease of reaching destinations and the interaction between the land-use and the transportation systems (Cerdá, 2009), while mobility is a measure of the performance of the transport system. Therefore, in comparison with mobility measures, accessibility measures are able to evaluate the interaction between transport and the spatial distribution of activities (Scheurer & Curtis, 2007).

Although increasing mobility will generally has a positive effect on the accessibility, it is possible to have high-quality mobility with low-quality accessibility or vice versa. For instance, an urban pattern with both traffic congestion and residents located within short distances of opportunities and desired destinations has low-quality mobility but high-quality accessibility. On the other hand, high-quality mobility does not guarantee high-quality accessibility. For instance, an urban area with low levels of congestion but with limited available opportunities for residents has high-quality mobility but inadequate accessibility (Handy, 2002). Consequently, planning with a focus on mobility may remedy only the congestion problems. Accessibility planning, however, can not only help to reduce automobile travel, but can also encourage travellers to use of alternative modes by reforming the land-use and transport policies together (Litman, 2003).

More recently, transit accessibility has become a leading global topic, with numbers of studies on public transit accessibility are increasing rapidly. Improving public transport is an essential concept in the sustainability, liveability, and welfare of cities, as it can improve mobility without imposing negative impacts on the economic and environment of cities. An accessible public transit system can also improve the liveability and welfare of citizens by improving equity, encouraging the social inclusions residents (e.g. carless, elderly, jobless), reducing cost of living (e.g. fuel, parking, car ownership expenses) as well as decreasing the negative impacts of using private vehicles on the environment (e.g. emissions, pollution, non-renewable resources) and on the urban transport (e.g. traffic congestion, road safety). Improvement of public transport can encourage communities to use and to rely on public transport, leading to a travel mode shift toward using public transport (Currie, 2004; Currie & Stanley, 2008).

As a result, transit accessibility as an important research direction attracted a lot of attention among researchers in transport planning, urban geography, and sustainable development. Public transport studies related to transit network design, transit system evaluation and land-use and transport planning in cities also require accurate transit accessibility measurement. Such measurement can be used to assess land-use and transport planning, evaluate social inequity in the transportation network, and understand barriers which transit users may face during their travel through the transit system (Cerdá, 2009).

A variety of transit accessibility measurements have been developed over the past five decades. However, reviewing the existing transit accessibility models in the literature shows that these approaches have almost failed to incorporate fine details of spatial-temporal transit coverage in a real network and pay little attention to travellers' behaviour and preferences in the transit system.

Thus, this research aims to explore the less researched aspects of the existing transit accessibility models in order to improve the model accuracy.

1.2.CONTEXT

One inherent characteristic that distinguishes public transit accessibility from accessibility for other transport modes is the complexities of public transport: the spatiotemporal limitations of the service, the importance of transfers, the multimodality of service, and the importance of strategic choices (Cats, 2011).

To trade off between modelling accuracy and maintaining the complexity manageable, a large body of research in the context of transit accessibility is focused on accessibility to the transit network, as a potential destination itself, rather than as a means of transport (Currie, 2010; El-Geneidy, Tetreault, & Surprenant-Legault, 2010; Murray, 2001; Polzin, Pendyala, & Navari, 2002). Although a main component of any transit journey is the access from the origin to the public transit corridor, the spatio-temporal characteristics of the transit network can also, effects transit accessibility significantly. To capture these complexities, a closer evaluation of transit accessibility by considering transit impedance through the entire transit network (including “first-and-last mile”) becomes critical.

Although some researchers have recently acknowledged the importance of accessibility through the transit network and to actual destinations but with a lack of detailed transit schedule information, generally they had to apply simplified transit cost calculations and estimate the travel time based on average route speeds, and route frequencies (Moniruzzaman & Páez, 2012; O'Sullivan, Morrison, & Shearer, 2000; Zhu & Liu, 2004), or simplifying assumptions regarding transfer waiting times (Lee, 2005; Mavoa, Witten, McCreanor, & O’Sullivan, 2012; O'Sullivan, et al., 2000; Tribby & Zandbergen, 2012; Yigitcanlar, Sipe, Evans, & Pitot, 2007) regardless of the time dependency in the service availability of transit services.

On the other hand, a recent body of research acknowledged and estimated accurate travel times but used schedule-based shortest path algorithms that calculated the fastest travel time between the origin-destination (OD) pair in the time-dependent transit network, with walk links for access, egress, and transfer interchanges (Church et al., 2005; Lei & Church, 2010; Lei, Chen, & Goulias, 2012; Salonen & Toivonen, 2013).

Although these recent class of measurements have been successful in calculating accurate time-dependent travel times in a transit network as a representation of impedance between O-D pairs, they have limited the perceived travel disutility of travellers to congestion levels and travel time only, to explain the actual network accessibility. These models ignored travellers’ preferences in a real transit network.

However, transit users may have different perceptions about different characteristics of public transit, such as frequency of transit services or average travel time and they behave differently in different situations.

However, due to inherent complexities of public transport, estimating transit network accessibility by considering the transit user behaviour and their subjectivity in perceptions of transit network would not be an easy practice.

As a result, this research aims to develop a practical transit accessibility model to capture these indeterminacies and to explore actual travellers' behaviours in the dense transit networks.

1.3.PURPOSES

Reviewing existing accessibility approaches, particularly the transit accessibility models, revealed that the drawback to these models is not limited to capturing the actual benefits that a traveller can gain from access to opportunities (benefit side). These models have other challenges that they do not aim to capture the actual travellers' preferences in the transit network and also they do not aim to underline the obstacles that travellers may face in their transit journey to opportunities. To address this gap, this research focuses on transit network accessibility, aiming to explain the actual impedance of transit network from transit users' point of view.

Therefore, this research aims to improve the accuracy of transit network accessibility model by capturing the following identified limitations and shortcomings in the existing transit accessibility measurements:

- Capturing the travellers' behaviour and the fine details of spatio-temporal characteristics of the transit system. Existing transit accessibility approaches have typically either proposed simple time-dependent measurements to explain the transit network accessibility or estimated transit accessibility only for measuring the accessibility to the transit corridors (transit stops). These simplifications cannot capture the effects of actual travellers' behaviour and their perception about the transit service characteristics.
- Capturing the benefits that the diversity of transit services (different available routes and transit mode options) can offer to the community.

The existing approaches did not aim to capture the perception of travellers about the diverse available alternatives in the transit network; focusing on only a single path to destination for accessibility estimation. As a result, these approaches could not describe the actual benefit or impedance of the transit network.

- Capturing stochasticity and subjectivity in perceptions of transit network among the transit users. Existing models ignored the stochastic error term that is known to exist in perceptions of transit network among transit users. These approaches also assume that all the travellers have the perfect knowledge about the transit network and they can choose the best route to the destination which it cannot be a true assumption.

Based on these defined goals, the following major objectives are set to achieve the research targets:

- Exploring the behavioural aspects of transit accessibility and the stochastic nature of path choice in the transit system
- Quantifying the total net benefit that residents of a particular geographic area can gain from the availability of a diverse set of paths or transit mode options.

Along with these key objectives, this research also sets the following secondary objectives:

- Establishing a framework to solve the difficulties with passengers' strategic boarding/alighting behaviour in high frequency transit network
- Rectifying the correlation between available transit mode services
- Rectifying the correlation among the path alternatives (path overlapping issue)
- Validating the developed model and transit accessibility results
- Exploring the model sensitivities to changes in the transit system
- Outlining possible improvement in the developed transit accessibility model.

1.4.SIGNIFICANCE, SCOPE AND DEFINITIONS

There is now broad agreement that the present trends in transport planning are not sustainable, and essential changes in the aspect of transport system are needed (Greene & Wegener, 1997). In response to these concerns, improving accessibility, in particular transit accessibility in cities, becomes a common aspect in the goals section of all transportation plans (Handy, 2002); transit accessibility becomes to be a fundamental element for overcoming current environmental concerns, social matters and economic inequalities (Bertolini, 2005).

On the other hand, complete transportation planning requires methods for assessing both the transit accessibility (Miller & Wu, 2000) and the desirability of public transportation from the passenger point of view. Recent evaluations of accessibility can be interpreted as transit behaviour models in which accessibility measurements enable better understanding of passengers' behaviour when using public transit systems. This view to transit accessibility measurements has become more critical as many current transportation planning has failed because of neglecting the travellers' behaviour (Gulhan, Ceylan, Özuysal, & Ceylan, 2013; Rastogi & Rao, 2002).

This research aims not only to capture travellers' behaviour and fine details of spatio-temporal characteristics of transit system but also to capture benefits of transit service diversities along with stochasticity in perceptions of transit networks among the travellers.

To move this research toward its goals, the scope of this study has been narrowed. This research focuses on capturing the transit network accessibility from origin to actual opportunities; the actual benefit that a traveller can gain from ease of access (benefit side) is not discussed in the research. It should also be noted that, contrary to existing research that accounts for the stochasticity of the transit services (Hickman, 2001; Hickman & Bernstein, 1997) or to approaches that consider stochasticity of passengers for the choice of destinations or travel modes (Bhat, Carini, & Misra, 1999; Bhat, Govindarajan, & Pulugurta, 1998; Davidson, 2008) , this research has assumed that the transit service is deterministic and that the model focuses on stochasticity in perceptions of transit network for travelling to a destination.

As a result, the significance of developing this transit accessibility measurement can be summarised under two categories:

1) Enabling transport and urban planners to have better understanding about actual transit accessibility (post-implementation stage) by capturing:
   - Complexities of transit users' behaviour in dense transit networks and also transit service characteristics, as perceived by transit users
   - Benefits of transit diversities or available transit options in the transit network
   - Stochasticity and subjectivity in the perception of transit network among transit users.
2) Developing a practical decision making tool to analyse passenger's behaviour and their perception about changes in the transit system at pre-implementation stage (transit network modelling analysis) and post-implementation stage by:
   - Quantifying different policies and scenarios (e.g. improving the transit service facilities, reducing the cost of the trip)
   - Exploring the success and risk of different policies and;
   - Identifying optimum solutions for improving the transit accessibility.

1.5.THESIS OUTLINE

Chapter two of this thesis, the literature review, first presents accessibility definitions (2.2.1) and accessibility components (2.2.2). Then the traditional accessibility models along with their advantages and limitations are evaluated and summarised in (2.2.3) and (2.2.4) respectively. Common limitations in the traditional accessibility models also are addressed in (2.2.5) before discussion of transit accessibility models and their limitations in (2.2.6). The next section, (2.3), provides a clarification about route choice approaches and it includes explanation about discrete choice approach (2.3.1), route set generation approaches (2.3.2), route choice models (2.3.3), route choice approaches and accessibility (2.3.4), and also transit route choice approaches (2.3.5). The conclusion, (2.4), covers the grounds and motivation for focusing on developing a model that will capture identified gaps in the existing transit accessibility models.

Chapter 3 introduces the model framework and choice model calibration. Firstly an overview of modelling structure (3.2) is explained. Then (3.3) presents the modelling specifications datasets used in this research including HTS (Household Travel Survey) Data, GTFS (General Transit Feed Specification) Data, GIS data of network and public transit facilities data. The next section,(3.4),describes the specification of the proposed access stop choice model an then (3.5) explains the proposed set generation algorithm and its generated choice sets. Path reasonability checks for the generated choice sets also are explained in this section. Section (3.6) presents the choice model calibration method and the results of the model calibration. Travellers' subjectivities and their stochasticity in perception of transit network are discussed in section (3.7). In section (3.8), the results of the proposed choice model are validated and, the last section (3.9) summarizes the outcomes of the chapter.

The logsum calculation for transit network accessibility will be explained in Chapter 4. In this chapter, the first section explains the development of a random utility-based measurement for the proposed transit accessibility model (4.2). The proposed model is then tested and visualised for the case study (Greater Brisbane) regarding accessibility to the Brisbane CBD (4.3.1) and accessibility to the Gold Coast CBD (4.3.2). The effects of travel costs on accessibility will also be discussed in these sections. The results of comparing the proposed accessibility model with simple travel time accessibility models will be also demonstrated in these sections. The estimated logsum values will then be validated by the residential land prices (4.4). The chapter concludes (4.5) with a summary of the benefits of the proposed transit network accessibility model.

In Chapter 5, after explanations about the policy sensitivity analysis and its application (5.1), the following sections propose five different scenarios for the sensitivity analysis: evaluating the model sensitivity to diversity of transit services (5.2.1) examining the sensitivity of model to changes in number of transfers in the transit network (5.2.2), Observing travellers' perception about stop amenities improvement (5.2.3), Assessing transit users' sensitivity to transit fare changes (5.2.4), Observing the model sensitivity and accessibility improvements by creating 15-minute walkable neighbourhoods to transit stops (5.2.5). Finally, section (5.3) provides a summary of the results of these sensitivity analyses.

Finally, Chapter 6 presents a summary of the main findings (6.2), including the common limitations of existing accessibility models (6.2.1) and the limitations of existing transit accessibility models (6.2.2), is presented first. Then, significance of the research is explained in section (6.3). The theoretical and practical contributions of this research are then summarized in (6.4.1) and (6.4.2) respectively. Section (6.5), provides a summary of individual chapters' contributions, following by the research limitations (6.6). New avenues are suggested for future research in the final section (6.7).

Chapter 2: Literature Review

2.1 INTRODUCTION

During the past few decades, a significant body of literature has contributed to quantifying urban accessibility and in particular transit accessibility. However, due to inherent complexities of public transport such as the spatiotemporal characteristics of the service, the importance of transfers, the multimodality of service, and the importance of strategic path choices (Cats, 2011), accurate estimation of the transit accessibility in real-sized and time-dependent networks has often been compromised.

Various accessibility approaches have proposed different methods to capture or manage these complexities but these approaches often fail to provide accurate estimations. For instance, a large body of literature in the context of transit accessibility is focused on accessibility to the transit network or access legs (Currie, 2010; El-Geneidy, et al., 2010; Murray, 2001; Polzin, et al., 2002) to improve the modelling accuracy by keeping the complexity manageable. However, these approaches overestimate transit accessibility by considering the transit stop as a potential destination, instead of as a means of transport (Lei & Church, 2010).

To understand why the existing transit accessibility models cannot provide an accurate estimation, it is essential to have a broad knowledge of the accessibility concept and its components, and to perform a comprehensive review about the existing models. Thus, the outcome of this review is to identify gaps in the existing transit accessibility models.

The literature review should also answer the following key questions:

- What are the weaknesses and limitations in the existing accessibility models, particularly the transit accessibility models?
- Can existing transit accessibility models capture travellers' behaviour in the transit system?
- Why it is important to incorporate travellers' route choice behaviour and preferences in the accessibility model?
- What are the major weaknesses in the transit path choice models?

Chapter Outline

In this chapter, accessibility definitions (2.2.1) and accessibility components (2.2.2) are presented first. The traditional accessibility models, along with their advantages and limitations, are then evaluated and summarized in (2.2.3) and (2.2.4) respectively. Common limitations in the traditional accessibility models are addressed in (2.2.5) before discussion of transit accessibility models and their limitations in (2.2.6). The next section, (2.3), provides clarification about route choice modelling and approaches, including the discrete choice approach (2.3.1), the route set generation approaches (2.3.2), the route choice models (2.3.3), the route choice approaches and accessibility (2.3.4), and the transit route choice approaches (2.3.5). The conclusion, (2.4), covers the grounds and motivation for focusing on developing a model that will fill identified gaps in the existing transit accessibility models.

2.2 REVIEW THE ACCESSIBILITY CONCEPT

2.2.1 Accessibility definitions

The concept of accessibility has been discussed in transportation literature for more than five decades (Horning, El-Geneidy, & Krizek, 2008). However, the accessibility concept is still difficult to define and measure (Handy, 2002; Lei & Church, 2010; Wang, Brown, & Mateo-Babiano, 2013). Accessibility definitions become very important because different accessibility concepts and measurements demonstrate their approaches to accessibility (Jones, 1981; Makri & Folkesson, 1999).

At the time of the introduction of the concept of accessibility in the 1950s and 1960s, it was acknowledged as an urban growth concept for controlling future urban development (Wegener, 1998). These definitions however have not focused on forecasting the development of cities; rather, they have attempted to explain the interaction between land use and transportation strategies, as well as socio-economic characteristics of residents (Geertman & Ritsema Van Eck, 1995).

Reviewing current accessibility definitions and approaches shows that as the concept of accessibility used in various studies such as socio-economic, transportation and urban planning (Doi, Kii, & Nakanishi, 2008), it can be defined in several ways.

A number of definitions focused only on **attractiveness of opportunities** for defining accessibility. Hansen (1959) defined it as 'the potential of opportunities for interaction'. Other revealed the interaction between **land use and transport system** by defining accessibility as 'the ease with which any land-use activity can be reached from a location using a particular transport system' (Dalvi & Martin, 1976) , 'the benefits provided by a transportation/land-use system' (Ben-Akiva & Lerman, 1985) , 'the amount and diversity of places that can be reached within a given travel time and/or cost' (Bertolini, 2005) and 'the consumer surplus, or net benefit, that people achieve from using the transport and land-use system' (Leonardi, 1978). Iacono, et al. (2010) described accessibility as a tool for monitoring land use and transportation system, and for assessing the effect of proposed policies and decision making on the land use or the transport network. Based on their definition, accessibility should describe the benefits of both transport and land-use planning together.

El-Geneidy and Levinson (2006); Burns (1980); Huisman (2005); Weibull (1980) moved one step forward, involving the effect of **individuals or socio-economic** variables. Burns (1980) defined accessibility as 'the freedom of individuals to decide whether or not to participate in different activities' while Weibull (1980) defined it as the freedom and ability of people to participate in different activities. Huisman (2005) viewed it as 'a significant concept employed to understand patterns in the location of facilities and to indicate broad features of the behaviour of people, as well as evaluating the ability of services to meet people's needs', while El-Geneidy and Levinson (2006) suggested it to be 'a measure or indicator of the performance of transportation systems in serving individuals living in a community'.

Bhat et al. (2000) added a **temporal** aspect to the accessibility definition, describing it as 'ease of an individual to pursue an activity of a desired type, at a desired location, by a desired mode, and at a desired time'. They defined accessibility by land-use attractiveness, transport system attributes, traveller's characteristics and temporal aspects of accessibility.

Some of the literature added further dimensions to the accessibility definition by introducing subsidiary notions. Ingram (1971) introduced 'relative accessibility', the level of connectivity between two location, and 'integral accessibility', the connectivity to all other locations in a given area. Handy (1992) defined 'local accessibility' as accessibility to nearby activities such as small shopping centres and supermarkets associated with short and frequent trips and ‘regional accessibility’ as accessibility to large shopping centres and commercial areas associated with long and infrequent trips.

Yet another dimension occurs between ‘Active accessibility’, a traveller’s desirability and ability to participate in different activities located in a given area, and ‘Passive accessibility’ ,the ease of reaching a place by different travellers in a given area (Cascetta, Cartenì, & Montanino, 2013; Hanson, 1995; Miller, 2007; Pirie, 1979).

The literature defined transit accessibility in a similar fashion by restricting the mode of travel to public transit and perhaps walking (Hillman & Pool, 1997; Murray, Davis, Stimson, & Ferreira, 1998; O'Sullivan, et al., 2000; Zhu & Liu, 2004). Ikhrata and Michell (1997) described transit accessibility as an evaluation of the transit system from the transit users’ point of view. This recent transit accessibility definition emphasised on transit users’ behaviour in the transit system.

From these definitions, we can derive four main components of the accessibility approaches. In the next section, these components are explained briefly.

2.2.2 Accessibility components

According to the literature, accessibility is affected by different aspects, including the interactions of various components such as transportation performance and individuals’ characteristics that are often difficult to estimate and analyse (Pirie, 1979; Pooler, 1987)

Although the accessibility concept definitions and measures introduced vary in their details, they consider two essential components. The first key component, the attractiveness of opportunities or land use effects, is usually measured as the number of opportunities at destinations. For instance, for accessibility to jobs, the attraction value can be defined as the number of employees at the different potential destinations, while for shopping centres this can be defined as the number of shops or the net floor area of the shopping centre. The second key component, the transport system, should explain the transport system characteristics and performances, such as total travel time, in-vehicle time and transport cost (Cerdá, 2009). Two additional components that considered in the accessibility measurements are the temporal and individuals’ characteristics. These four accessibility components are described below.

1. The **attractiveness of opportunities or land-use** component describes the land-use condition, including the quantity of opportunities, the quality of land-use, the spatial distribution of opportunities and the competition between supply and demand, such as competition for job or school vacancies (Geurs & Van Wee, 2004). Accessibility models typically apply a weight factor to the opportunities to demonstrate their attractiveness for the people in a given area.

2. The **transport** component represents the transport supply attributes and the performance of the transport system, such as travel time, cost of travel, reliability and level of comfort (Geurs & Van Wee, 2004). It should be noted that this accessibility is directly affected by transport system performance.

3. The **temporal** component describes the temporal constraints, such as the availability of opportunities at different times, and the time availability for people to take part in various activities (Geurs & Van Wee, 2004). Generally, we can include the temporal effects by estimating the accessibility within a pre-set time of travel, for example in the morning peak (Cerdá, 2009).

4. The **individual** component represents the travellers' characteristics and abilities, such as the socio-economic characteristics of individuals and their physical abilities. This component is important as travellers' abilities and preferences can affect their level of access to transport system and opportunities (Cervero, Rood, & Appleyard, 1995; Geurs & Van Eck, 2003; Geurs & Van Wee, 2004; Shen, 1998).

Table 2-1 shows these accessibility components and level of their contributions in various accessibility approaches.

2.2.3 Traditional accessibility measurements and approaches

The first step for developing a more accurate measurement for accessibility is to understand their limitations and the theoretical concepts behind the existing models. Since definition of accessibility approach, various measurements have been introduced and developed over the past six decade. These measurements, generally classified into six main categories, are introduced in the following section.

Distance measurements

Distance measures, the easiest accessibility measurement, simply incorporate the distance from a given origin to different opportunities into the model. The distances in these models can be estimated as the average distance to opportunities in a given area or the distance to the closest opportunity. Some studies have proposed simple straight-line (Euclidean) distances; others have proposed complicated impedance formulations for weighting the distance to opportunities. Reviewing the distance measurements also shows that some approaches have suggested using either an average distance to a destination from all origins, or the average distance to all destinations from an origin, to estimate the distance attribute in the distance accessibility measure (Makri & Folkesson, 1999). More complex models proposed calculating the distance in relation to the topological network (Pooler, 1987). Hence, the distance estimation methods can be summarised into five categories (Geurs & Van Wee, 2004; Makri & Folkesson, 1999):

- Euclidean distance
- Network distance or topological distance
- Network travel time (constant speed, single mode)
- Dynamic network travel times (single mode)
- Dynamic, multi-modal network travel times.

This type of accessibility measurement is usually given by:

$$A_i = \sum_J D_{ij}^{-k} \qquad (2\text{-}1)$$

where:

A_i Accessibility of zone *i*

D_{ij} Distance from the centre of zone i to the centre of zone j

J Set of zones

$-k$ Distance decay weighting on the accessibility of zone *i*

The distance decay weighting has provided a measure for the spatial aspects of travel, which can be estimated for each trip mode. It has also presented a gauge to capture travellers’ behaviour with respect to perception of distance (Iacono, Krizek, & El-Geneidy, 2008).

Advantages and Limitations of Distance Measures

The benefits of distance measurements are their simplicity and practicality. These measurements are relatively simple in terms of data collection and are easy to understand by decision makers, as they capture only the effect of distance from the opportunities with an easy approach (Geurs & Van Wee, 2004).

However, the distance models have several drawbacks. First, these measurements could not capture the combined effect of land-use and transport attributes, as they are not capable of incorporating the effect of land-use supply and demand into the model (e.g. the spatial distribution of the demand and the capacity restrictions of supply in hospitals). This measurement can estimate only the impedance part of the accessibility. A second criticism of these measures is that they could not capture travellers' preferences and behaviour. These measurements assumed that all opportunities are equally desirable for all of individuals, regardless of travellers' abilities and preferences (Geurs & Van Wee, 2004).

Cumulative Opportunity Measures

The cumulative opportunity measurement, also called the contour measure, the isochronic measure or the daily accessibility, is another simple accessibility model in terms of calculation technique (Geurs & Van Wee, 2004; Wachs & Kumagai, 1973). These models generally described the accessibility for a given origin as the number of opportunities accessible within a fixed travel time, distance or cost. Another method applied in this approach is to calculate the time or cost required to reach a fixed number of opportunities. For instance, the accessibility can be estimated as the numbers of shops within 20 minutes, travel time from an origin by a certain mode of trip, or it can be calculated as time which a traveller required to reach a fixed number of shops in a given area (Envall, 2007; Geurs & Van Wee, 2004). Breheny (1978) and Envall (2007) noted three main forms of cumulative opportunity measures: Fixed opportunities measured the total impedance (time, distance or cost) for reaching to the fixed number of opportunities; Fixed impedances accounted for the total number of opportunities located within a particular distance, time or cost; fixed population measured the average number of available opportunities (over the population) within fixed travel costs. This type of accessibility measure is generally given by:

$$A_i = \sum_{j=1}^{J} B_j a_j \qquad (2\text{-}2)$$

where:

A_i Accessibility measure at point ***i*** to potential activity in zone ***j***

a_j Opportunities in zone ***j***

B_j Incident value; equal to ***1*** if zone ***j*** is within the predetermined threshold and ***0*** otherwise.

Advantages and Limitations of Cumulative Opportunity Measures

A potentially strong point of cumulative opportunity measurements is that they are simple to understand and relatively easy to apply to different travel modes. However, similar to distance measurements, they cannot explain the attractiveness of opportunities, as they assume that all opportunities have the same importance and attractiveness in the travellers' perception. These models are unable to clarify how travellers prefer and value particular opportunities (El-Geneidy & Levinson, 2006; Makri & Folkesson, 1999). To treat this limitation, a number of researchers took the spatial distribution of land-use into account, proposing to give a small weight to opportunities located distant from the given origin (Black & Conroy, 1977), but this simplicity in estimating the attractiveness of opportunities cannot capture the actual benefits of destinations from the perception of travellers. The cumulative measurements also are unable to capture the travellers' perceptions and preferences (Geurs & Ritsema van Eck, 2001; Geurs & Van Wee, 2004).

Another drawback to these models is that they are very sensitive to pre-defined (cut-off) areas: that is, any change to the cut-off area would have a strong effect on the modelling. For instance, a small variation in time or distance (an arbitrary calibration) can increase the number of available opportunities considerably (Ben-Akiva & Lerman, 1979; Envall, 2007; Makri & Folkesson, 1999).

Gravity-Based Measures

Gravity-based measures or potential accessibility measures were introduced and developed by Hansen (1959) from the denominator of the gravity model for trip distribution. These gravity-based models proposed a weight to opportunities for representing their attraction and considered an impedance value (decay function) to reflect their distance from origins. Gravity-based models differ in the method adopted for the decay function calibration as well as for calculating the attractiveness of opportunities (Dong, Ben-Akiva, Bowman, & Walker, 2006; El-Geneidy & Levinson, 2006; Geertman & Ritsema Van Eck, 1995; Makri & Folkesson, 1999).

To achieve reasonable results in gravity models, it is very important to choose and calibrate an adequate impedance function to reflect travellers' behaviour in a given area (Geurs & Van Wee, 2004). To estimate the impedance function based on travellers' behaviour, a number of researchers applied experimental and statistical techniques such as Maximum Likelihood Estimation (Flowerdew & Aitkin, 1982; Sen & Matuszewski, 1991) and Ordinary Least Squares (Fotheringham & O'Kelly, 1989).

Ingram (1971) proposed a Gaussian curve based on trip frequency data versus trip length in minutes for the distance decay function. For improving the gravity-based measurements, Bruinsma and Rietveld (1998) proposed replacing the impedance function by a generalized measure of travel costs such as time, distance, fares or waiting times. Handy and Niemeier (1997) and Kwan (1998) claimed that the negative exponential function can be fitted meaningfully to travellers' behaviour. However, it is important to point out that calibration based on actual travel behaviour has limitations, as the exposed behaviour may not necessarily show the preferred behaviour (Handy & Niemeier, 1997). For example, people may walk a long way to transit stops as they have no other choice for boarding the transit.

Gravity models can be explained by the following equation, which discounts the attraction between origin and destination by a distance decay function:

$$A_i = \sum_J O_j f(C_{ij}) \qquad (2\text{-}3)$$

where:

A_i the accessibility at point ***i*** to potential activity at point ***j***

O_j the opportunities at point ***j***

$f(C_{ij})$ the impedance or cost function to travel between ***i*** and ***j***

Therefore, the gravity models can capture the combine effects of land-use, represented by O_j, and transportation, represented by $f(C_{ij})$.

The typical gravity measures did not consider the spatial imbalances of demand or supply. For example, employees would compete with each other for finding jobs; businesses may compete with each other for attracting customers or employees (Geurs, van Wee, & Rietveld, 2006). Geurs, et al. (2006) acknowledged three approaches for including the effects of competition between opportunities in gravity models. In the first approach introduced by Knox (1978), Weibull (1976) and developed by Van Wee, Hagoort, and Annema (2001), they proposed dividing the supply values within reach from origin (zone *i*) by a demand likelihood from zone j. This approach is applicable if origin and destination are located not far from each other.

The second approach, introduced by Breheny (1978) and Shen (1998), proposed to apply a possible supply for origin *i* and the potential demand of those opportunities from each destination j. This approach is applicable while competition affects the opportunity side or where available destinations such as schools or health-care facilities have restrictions on the number of students or patients. This approach proposed incorporating the demand potential in the model by dividing the overall number of supply at zone *j* by the total number of demand in zone *j*. The measure is formulated as:

$$A_i = \sum_J \frac{O_j f(C_{ij})}{D_j} \qquad (2\text{-}4) \qquad , \qquad D_j = \sum_J P_j f(C_{ij}) \qquad (2\text{-}5)$$

where:

A_i the accessibility at point ***i*** to potential activity at point ***j***

O_j the opportunities at point ***j***

$f(C_{ij})$ the impedance or cost function to travel between ***i*** and ***j***

D_j the demand for the opportunities

P_j the number of people in location ***j*** seeking the opportunities

The final approach is based on balancing factors which introduced by Wilson (1970, 1971). In this interaction model the balancing factors guarantee that the population movement from origins to destinations equals the actual number of activities in the origins (El-Geneidy & Levinson, 2006; Geurs, et al., 2006). In this measurement, known as the double constrained spatial interaction model, the supply and demand potential for all the zones needs to be calculated iteratively to ensure that the number of trips to and from each zone is equivalent to the number of possible opportunities (Geurs & Van Eck, 2003).

This approach was developed from a transport and land use interaction concept (Geurs & Van Wee, 2004) in which the general trip distribution formula can be described as:

$$T_{ij} = A_i B_j O_i D_j \exp(-\beta c_{ij}) \quad (2\text{-}6)$$

where:

T_{ij}	the number of trips between origin *i* and destination *j*
O_i	the trips originating at *i*
D_j	the Trips destined for *j*
c_{ij}	the (generalised) costs of travel (for example, time and trip costs) between zones i and j
β	the cost-sensitivity parameter

A_i and B_j are the factors to ensure that

$$\sum_j T_{ij} = O_i \quad (2\text{-}7) \quad \text{and} \quad \sum_i T_{ij} = D_j \quad (2\text{-}8)$$

hence:

$$A_i = \frac{1}{\sum_j B_j D_j \exp(-\beta c_{ij})} \quad (2\text{-}9) \quad \text{and} \quad B_j = \frac{1}{\sum_j A_i O_i \exp(-\beta c_{ij})} \quad (2\text{-}10)$$

Replace A_i and B_j by inverted factors a_i and b_j to balancing factors.

$$A_i = \frac{1}{a_i} \quad (2\text{-}11) \quad \text{and} \quad B_j = \frac{1}{b_j} \quad (2\text{-}12)$$

Hence, the balancing factors have been defined in the following equations (Geurs & Van Wee, 2004):

$$a_i = \sum_{j=1}^{n} \frac{1}{b_j} D_j \exp(-\beta c_{ij}) \qquad (2\text{-}13)$$

$$b_j = \sum_{i=1}^{m} \frac{1}{a_i} O_i \exp(-\beta c_{ij}) \qquad (2\text{-}14)$$

where:

O_i the numbers of opportunities at origin i

D_j the distance to destination j

c_{ij} the (generalised) costs of travel (e.g. time and trip costs) between zones i and j

β the cost-sensitivity parameter.

Estimating the balancing factors a_i and b_j is an iterative process that needs to be continued until equations are being converged. These balancing factors allow the model to include the competition effects between supplied opportunities and origin demands. As a result, this method can be used adequately when competition effects appear on both sides (origin and destination), such as in job accessibility (Geurs & Van Wee, 2004).

Advantages and Limitations of Gravity-Based Measures

The practical advantage of gravity measurements is that they can easily incorporate land-use and transport components. Another benefit of gravity-based measures is that they can capture the discounting role of distance on opportunities (without artificial thresholds), as distant opportunities have less attraction for travellers (Geurs & Van Wee, 2004). This is a significant advantage in these models, because accessibility measures should capture the travellers' perceptions about surrounding environment (Handy & Niemeier, 1997).

A potential limitation in these models is related to defining an appropriate impedance function (El-Geneidy & Levinson, 2006; Envall, 2007). This issue becomes more important when decay functions are calculated empirically to evaluate various scenarios for different spatial distribution, different travel patterns or different modes of travel (Geurs & Ritsema van Eck, 2001). These models are limited in their ability to capture the travellers' behaviour accurately in the estimation of model impedance. Although a number of scholars (Handy & Niemeier, 1997; Kwan, 1998) claim to have found the appropriate model curve to fit with the impedance function, the exposed behaviour could not essentially show the travellers' behaviour (Handy & Niemeier, 1997) as people may walk a long way to a transit stop if they have no other alternative for reaching the transit corridor.

Another shortcoming of this measurement is in finding appropriate weights for attractiveness of opportunities, as existing gravity models do not have an established method for estimating the attractiveness of opportunities. For example, these models usually apply a quantitative approach (e.g. number of shops or number of employees) to weight the destinations, ignoring the qualitative effects of the attractiveness of opportunities.

A further point of criticism in these models is related to model limitation to capture travellers' characteristics as estimated accessibility value for all residents within a zone would be identical in the gravity model (Ben-Akiva & Lerman, 1979). However, in a real network, travellers may have different levels of accessibility due to their personal characteristics and physical abilities. A location may provide a high level of accessibility to jobs, but travellers with physical disabilities may still have a low level of accessibility to employment.

A final criticism to gravity models is that combination of modes is not easy in these models while the decay functions should be estimated for different mode of travel (El-Geneidy & Levinson, 2006).

Utility-Based Measures

Utility-based accessibility measures, first introduced by Ben-Akiva and Lerman (1979), have been widely used in different urban and transportation studies (Bhat, et al., 1999; Bhat, et al., 1998; Chen, Yang, Kongsomsaksakul, & Lee, 2007; Gulhan, et al., 2013; Koenig, 1980). This model is defined based on the "logsum" expression of a random utility model in which the probability of an individual making a particular choice is related to the utility of all choices (Ben-Akiva & Lerman, 1985). The theoretical basis of utility models is directly linked to economic theory and is consistent with the key concept of the total consumer net benefit. In this theory, individuals gain the utility by proximity to urban opportunities reachable within a given travel expense (Cascetta, et al., 2013; Hansen, 1959). Based on economic benefits theory, people can gain benefits when they have access to opportunities (El-Geneidy & Levinson, 2006).

Given that travellers perceive the utility of opportunities in different ways, the logsum approach can be an effective technique that provides an estimate of an expected maximum utility, based on the choice set available to them. Utility models are based on two assumptions: first, individuals choose an alternative associated to the maximum utility for them; second, it is not realistic to assume that people or planner can estimate all the factors which contribute to the utility of a destination (Ben-Akiva & Lerman, 1985; Koppelman & Bhat, 2006). Thus, the utility function can be described as the sum of non-random (deterministic) and random (stochastic) components (Koenig, 1980). The accessibility is defined in a general discrete choice model as follows.

$$A_n = \sum_{i \in C} U_{in} = \sum_{i \in C} (V_{in} + \varepsilon_{in}) \qquad (2\text{-}15)$$

where

A_n the perceived accessibility by person n,

C the set of all available choices,

U_{in} the actual utility of choice i perceived by person n,

V_{in} the systematic utility

ε_{in} the random component

The accepted concepts and calculation methods for estimating the random component of discrete choice models will be explored in discrete choice approaches.

One of the advantages of utility-based models is their capability to capture the benefits of opportunities. Similar to double constrained entropy or balancing approaches in the gravity-based models, Martínez and Araya (2000) proposed to incorporate the effect of land-use supply and demand into the model by applying the balancing factors to utility model as follows:

$$a_i = \sum_{j=1} \frac{1}{b_j} D_j \exp(-\beta c_{ij}) \qquad (2\text{-}16)$$

$$b_j = \sum_{i=1} \frac{1}{a_i} O_i \exp(-\beta c_{ij}) \qquad (2\text{-}17)$$

Advantages and Limitations of Utility-Based Measures

Utility measures could find and estimate the best utility function which fits to actual traveller's behaviour. This measure can incorporate travellers' characteristics and transport features by analysing the impact of various socio-economic attributes such as car ownership, employment status, income, household structure, travel times and costs. This makes the utility measurement a proper tool to evaluate the impacts of policy changes on different travellers, especially disadvantaged groups (Cerdá, 2009). However, capturing all attributes which may affect the perception of utility among travellers is one of the main challenges in these models. The existing utility-based models also assume that people have perfect knowledge for all of their available options and that they choose an alternative which provides them the maximum utility. However, in a real network people may not have a complete knowledge about the network and choose different alternatives in different conditions (Nassir, Ziebarth, Sall, & Zorn, 2014).

Another limitation with utility-based measurements is related to their inherent difficulties in interpreting and understanding the calculated multi-dimensional logsum values (Koppelman & Bhat, 2006). This issue is elaborated in Chapter 4 by providing some examples (Table 4-1) for the calculated logsum values.

Capturing the random nature of users' preferences and their demand to extensive high-resolution data (Geurs & Van Wee, 2004) are other challenges in the utility-based accessibility models.

Space-time measure

The concept of space-time measures also known as people-based measurement was introduced by Hägerstraand (1970) and developed by Lenntorp (1977). The space-time models incorporated the spatial and temporal aspects of accessibility (Cerdá, 2009). Generally, participating in an activity needs to be at a given location and a given time (Miller, 2007). This measurement shows the possibility of an individual participating in an activity by using the space-time prism as an accessibility indicator

(Makri & Folkesson, 1999). In these models, it is assumed that the amounts of time available to participate in different activities are restricted by different criteria (Miller, 1999). Hägerstraand (1970) defined three constraints for restricting the space-time prism:

- Capability constraints
- Coupling constraints
- Authority constraints

Capability constraints represented time budget or distance restriction which an individuals' accessibility is limited due to that (e.g. individuals' physical abilities for walking). Also, other individuals' physiological requirements such as sleeping can limit individuals' ability to participate activities in a given area. Coupling constraints represented spatial and temporal requirements which allow an individual to join people to perform different activities such as attending in school. Authority constraints represented the general law which restricts individuals access to locations such as military bases or time period such as opening time for business centres (Makri & Folkesson, 1999; Miller, 2007; Miller, 2005). Hägerstraand (1970) also noted that activities can be either fixed or flexible. For instance, going to school is a fixed activity; however, people can start shopping any time of day (Cerdá, 2009).

The space-time prism in this measure represented the area which an individual can move during a time budget to participate in various activities. In other words, a place can be reached by an individual during a day, should be located in his/her space-time prism (Miller, 2007). Projecting the space-time prism onto a two-dimensional geographic space generates the potential path area (PPA), which shows the area containing all the activities an individual can participate in or all destinations can be visited by an individual at given space-time prism (Kwan, Murray, O'Kelly, & Tiefelsdorf, 2003; Miller, 2007). Therefore, the space-time prism is defined as a tool for accessibility measurement by calculating the number of available opportunities to an individual (Kwan, 1998; Weber & Kwan, 2002).

As a result, the space-time prism should determine the possible locations for the space-time path. As shown in Figure 2-1, a space-time prism anchored by fixed activities has only one spatial alternative within given time. For example, Figure 2-1 is shown two anchor points: the individual's home where s/he should leave no earlier than time ***ti*** and the work place which s/he must be no later than time ***tj***. During the time interval ***tij = (tj- ti)***, the individual can stop at several locations to perform activities. The points inside the time-space prism represent the spots which the person can occupy during the travel period and the paths represent his/her travel routes between these locations. Therefore, an individual cannot participate in any activities outside of the potential path area (Miller, 2007; Miller, 2005).

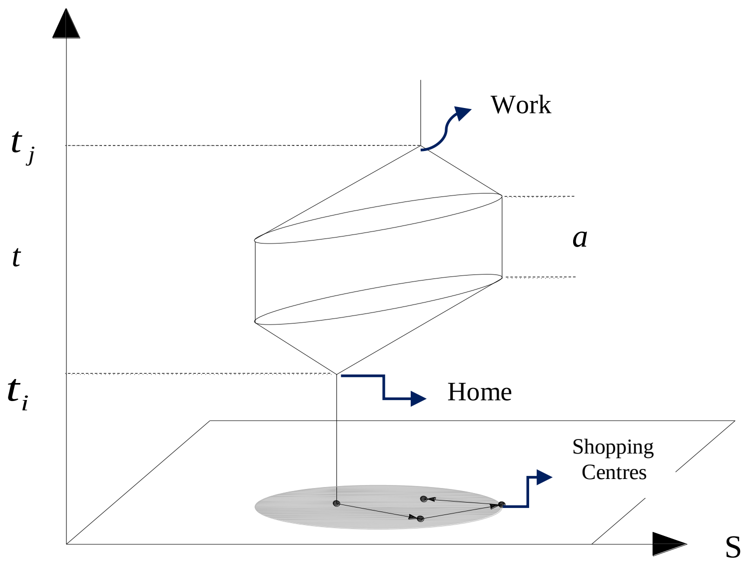


Figure 2-1: Schematic Space-Time Prism (Miller, 1999)

Time-space models try to include all variables that restrict the freedom of travellers over time and space. In this regard, researchers have developed various GIS methods that incorporate the spatial distribution of destinations, the travel speeds and the transport system characteristics into the model (Kim & Kwan, 2003; Miller, 1999; Miller & Wu, 2000).

Advantages and Limitations of Space-Time Measures

A potentially strong point of a space-time model is the ability to incorporate temporal, individual, land use and transport components into the model. However, this requires very detailed and high-resolution trip data. This approach can be utilised for only a limited number of individuals (Cerdá, 2009), so it is not a practical model for a real network with numerous travellers. While other accessibility measurements can be visualised easily, however, visualizing the output of the model in space-time measures is not easy (Makri & Folkesson, 1999). These measures are probably the most appropriate model to understand the individual-level of accessibility and to evaluate the socio-economic characteristics of travellers, but they are not able to capture all the network and transport characteristics. The model difficulties in aggregating the accessibility results for different trip modes or trip purposes are another point of criticism in these models (Miller, 1999).

Place Rank Measure

The place rank measure developed based on a methodology, introduced by Brin and Page (1998), for ranking web pages for large-scale search engines. Ranking of web pages is associated with the number of links connecting to them. In this regard, they proposed to rank the opportunities based on the number of people reaching to them and translate this into the accessibility measurement. Place rank is an accessibility measure that requires the information of origins and destinations. This measure is based on the flows between origins and destinations and it considered the number of opportunities that a person discounted in a zone to reach an opportunity in another zone. Therefore, the power of individuals is related to the attractiveness of their zones of origin (El-Geneidy & Levinson, 2006). The mathematical formulation of the model is as follows:

$$R_{j,t} = \sum_{i=1}^{I} E_{ij} \times P_{it-1} \qquad (2\text{-}18)$$

$$P_{it-1} = \left[E_j \times \left[{R_{j,t-1}} \big/ {E_i} \right] \right] \qquad (2\text{-}19)$$

where:

$R_{j,t}$ the *place rank* of ***j*** in iteration ***t***

I the total number of ***i*** zones that are linked to zone ***j***

E_{ij} the number of people leaving ***i*** to reach an activity in ***j***

P_{it-1} the power of each person leaving ***i*** in the previous iteration

E_j the original number of people destined for ***j***: $E_j = \sum_i E_{ij}$ (2-20)

$R_{j,t-1}$ the place ranking of ***j*** from the previous iteration

E_i the original number of people residing in zone ***i***: $E_i = \sum_j E_{ij}$ (2-21)

Based on the above formulation, place rank reallocated the total number of people involved in the activity between the zones according to the attraction of the zone and the power of the links. The place rank value is estimated when either the variance between two repeated ranking calculations approaches zero or the model reaches stability (El-Geneidy & Levinson, 2006).

Advantages and Limitations of Place Rank Measures

The place rank measurement is based on travellers' choices for actual origins and destinations which represented land-use and transportation interactions by ranking the attractiveness of zones. The key benefit of this model is that having the impedance and travel times embedded in the model calculation removes the need for any experimental calibration. It also included both supply and demand for given activities as the model estimation is based on the people participating in the activities and the opportunities available to them (Cerdá, 2009). Although place rank measure is a practical method when both supply and demand (e.g. job opportunities and residents) are located in a same area, the main drawback in a real network is that zones are usually homogenous: that is, with either numerous opportunities and a few or no residential area, or numerous residents and a few or no opportunities (El-Geneidy & Levinson, 2006). The computing complexity of this model and its inability to observe travellers' characteristics are further shortcomings.

2.2.4 Summary of traditional accessibility approaches

Huisman (2005) classified the current accessibility models into three levels, shown in Figure 2-2. Level 1 includes the location-based accessibility measures, which proposed a simple measurement for spatial distribution of opportunities. These measures could not capture traveller's socio-economic and transport characteristics, and focus only on estimating the impedance function based on fixed distance, time or cost of travel. These models are usually very sensitive tools to show the effect of infrastructure investments on improving the accessibility (Cerdá, 2009).

As shown in this ranking, individual-based models can be placed in the second level of model complexities. These models can capture the transport attributes and individuals' characteristics; however, they propose more complex models, compared with the first level of models (Huisman, 2005). Individual-based models are useful tools to evaluate the accessibility for various individuals with different socio-economic characteristics in a region (Cerdá, 2009). The final category of accessibility measures in this ranking includes activity-based or behavioural-based models. These models incorporated different aspects of travellers' behaviour which cannot be captured in traditional accessibility measures. These measures also provided practical solutions for evaluating the effect of policy changes on different groups of people (Cerdá, 2009).

This review of the current accessibility approaches is shown that the practicality level of models is reversely proportional to the number of accessibility components or attributes which they can capture. This review has also revealed that different measurements are used to measure the accessibility in a particular geographical scale. For example, space-time approaches typically estimate accessibility at the level of neighbourhood and urban area, while gravity models tend to measure the accessibility at the regional level.

LEVEL 1		**Location-based models** • Fixed time/ cost or distance • Fixed trip mode • Fixed purpose of trips
LEVEL 2	**Complexity**	**Individual-based models** • Based on travel time • Fixed or calibrated mode availability • Considered individuals' characteristics • Considered attractiveness of opportunities
LEVEL 3		**Activity-based models** • Observed actual activities/trips • Considered actual mode choice • Considered actual time/cost/ distance • Observed household attributes • Observed temporal attributes

Figure 2-2 : Summary of current accessibility models (Huisman, 2005)

Table 2-1 shows the various accessibility models versus their incorporated components and the level of their satisfaction, based on primary research carried out by (Geurs & Van Wee, 2004).

Also, the advantages and limitations of traditional accessibility models are summarized in Table 2-2. As shown in Table 2-2, distance measures and cumulative opportunity measures can only partially describe the effects of transport and temporal components, gravity-based and utility-based models can capture the effects of land-use, transport, temporal and individual components on the accessibility outputs.

Reviewing the benefits and disadvantages of accessibility models has revealed common limitations which can generally be found in all accessibility models. These limitations are described in the following section.

Table 2-1: Components of accessibility measurements (Geurs & Van Wee, 2004)

Accessibility Measure	Level of Satisfaction & Attributes	Components: Transport	Land use: Demand	Land use: Supply	Temporal	Individual	Practicality
Distance Measures	*Level of Satisfaction*	◐	○	○	◐	○	●
	Indicators/Trip mode	• Transport (distance or time to destinations) • All modes					
Cumulative Measures	*Level of Satisfaction*	◐	◐	○	◐	○	●
	Indicators/Trip mode	• Transport (distance or time or cost to destinations) • Land use (excluding the attractiveness of supply) • Single mode					
Standard Gravity Measures	*Level of Satisfaction*	●	●	○	◐	○	●
	Indicators/Trip mode	• Transport (distance or time or cost to destinations) • Land use (excluding the attractiveness of supply) • Single mode					
Gravity Measures (Opportunities Dividing/ Opportunities Quotient/ Balancing Factors)	*Level of Satisfaction*	●	●	●	◐	○	●
	Indicators/Trip mode	• Transport (distance or time or cost to destinations) • Land use (including the attractiveness of supply) • Competition between land use(opportunities) • Single mode					
Utility Measures (Logsum Benefit Measure)	*Level of Satisfaction*	●	●	○	◐	●	●
	Indicators/Trip mode	• Transport(cost to destinations) • Land use (excluding the attractiveness of supply land use) • Individuals (socioeconomic characteristics of the individual) • All modes					
Utility Measures (Balancing Factor Benefit Measure)	*Level of Satisfaction*	●	●	●	◐	●	●
	Indicators/Trip mode	• Transport (cost to destinations) • Individuals (socioeconomic characteristics of the individual) • Land use (including the attractiveness of supply) • Competition between land use (opportunities) • All modes					
Place Rank Measure	*Level of Satisfaction*	◐	◐	◐	◐	○	◐
	Indicators/Trip mode	• Individuals (number of people of origin and destined) • Competition between districts • All modes					
Space-Time Measure	*Level of Satisfaction*	●	●	○	●	●	◐
	Indicators/Trip mode	• Transport (time to destinations) • Land use (excluding the attractiveness of supply) • Individual (individuals attributes) • Temporal(availability of opportunities at different times) • All modes					

● Completely satisfied ◐ Partly satisfied ○ Not satisfied

Table 2-2: The summary of advantages and the disadvantages of accessibility models

Model	Advantages	Disadvantages	Comments
Distance Measures	• Collecting input data is easy. • It is not difficult to analysis and present. • Applied easily to different modes.	• Paid no attention to land use and individual components and couldn't capture the effect of transport attributes properly. • Problem in selecting proper distance decay function. • Ignored size of opportunities (attractiveness) and competition between them.	Five types of measure are : • Euclidean distance • Network distance or topological distance • Network travel time (constant speed, single mode) • Dynamic network travel times (single mode) • Dynamic, multi-modal network travel times.
Cumulative Measures	• Simple to analysis & present • Applied easily to different modes. • Considered the transportation and land use components without any implicit assumptions. • Easy to interpret and understand.	• Defined solid & artificial boundary (cut-off area) for catchment area. • Problem in calibrating appropriated impedance indices. • Paid no attention to size of opportunities (attractiveness) and competition between them. • Ignored the temporal, individual components.	There are three main types of cumulative opportunity measures: • Fixed impedances (time, distance or cost), • Fixed opportunities and, • Fixed population.
Standard Gravity Measures	• Considered the diminishing role of opportunities' distance (without artificial thresholds) • Considered the transportation and land use components.	• Difficulties in calibrating an adequate impedance function • Ignored competition effects between opportunities. • Problem with weighting the opportunities. • Difficulties in combination of modes. • Ignored the temporal and individual components.	• Ingram (1971) concluded that a Gaussian curve distance decay function provided the best fit with trip frequency data over trip length in minutes. • Three options to solve the competition effects problem are: Opportunities dividing, opportunities quotient & balancing factors.
Gravity Measures (Opportunities Dividing)	• Included the diminishing role distant opportunities (without artificial thresholds) • Easy to compute by using existing land-use and transport data. • Considered competition between opportunities.	• Difficulties in calibrating adequate impedance function. • Problem with weighting the opportunities. • Difficulties in combination of modes • Paid no attention to temporal and individual components.	• This approach is fitted if the travel distance between origins and destinations is relatively small, such as for elementary schools or local shops (Geurs, et al., 2006).
Gravity Measures (Opportunities Quotient)	• Involved the diminishing role distant opportunities (without artificial thresholds) • Easy to compute by using existing land-use and transport data. • Considered competition between opportunities.	• Problem in calibrating an adequate impedance function. • Difficulties in weighting the opportunities. • Difficulties in combination of modes • Ignored temporal and individual components.	• This approach is beneficial for the analysis of accessibility to destinations where competition effects occur on destination locations or while opportunities have capacity limitations (e.g. recreational or health-care facilities).

Table 2-2: (continued)

Model	Advantages	Disadvantages	Comments
Gravity Measures (Balancing Factors**)**	• Considered the diminishing role distant opportunities (without artificial thresholds). • Considered competition between opportunities completely. • Enabled measurement to use land-use and transport demand models.	• Difficulties in calibrating adequate impedance function. • Difficulties in combination of modes. • Paid no attention to temporal, individual components. • Difficulties in weighting the opportunities.	• The balancing factor models are useful models in analysing accessibility to opportunities while competition effects happen on both sides (origin and destination) such as accessibility to jobs, while employees compete with each other for finding the jobs and employers compete with each other for employees (Geurs, et al., 2006).
Utility Measures (Log sum Benefit Measure)	• Based on strong theoretical concept. • Enabled to test utility functions to find the best matches for actual travel behaviour. • Considered socio-economic characteristics of travellers as well as temporal and transport characteristics.	• Ignored the competition effects between land use supply and demand.	• Utility-based models are based on economic benefits that people get the benefit from having access to certain activities (El-Geneidy & Levinson, 2006).
Utility Measures (Balancing Factor Benefit Measure)	• Included competition between opportunities completely. • Enabled to test utility functions to find the best matches for actual travel behaviour. • Considered the socio-economic characteristics of travellers. • The balancing factors are mutually dependent.	• Difficulties in collecting proper data for trip attraction and production for different mode of travels. • Computational complexity.	• Martinez (1995) and Martinez and Araya (2000) obtained the following accessibility measures from Williams' (1976) integral transport-user benefit measure.
Place Rank Measure	• Independency of any experimental calibration. • Applied easily to different trip modes. • Considered land-use and transportation interactions.	• It is only practical for homogenous land-use regions. • Ignored individual and temporal components. • Measure is relatively complex as it is the outcome of an iterative process. • Place rank measures only work while there are both opportunities and origins in a geographic region.	• The place rank measure is derived from methodology introduced by Brin and Page (1998) that is used in ranking web pages for search engines (Brin & Page, 1998).
Space-Time Measure	• Included temporal, individual & transport components. • Utilized for different trip modes.	• The model is not easy to estimate and present for the real network. • Difficulties in collecting high-resolution input data. • Paid no attention to competition effects between opportunities.	• All different measurements which derived from Space-Time theory proposed complex methods for computing the accessibility.

2.2.5 Common limitations of accessibility models

Regardless of the approach for measuring the accessibility, existing models deal with several challenges, as described below.

Collecting appropriate data

Data collection for accessibility measurements has several limitations. The first issue relates to obtaining high-resolution data, as some methods require high-resolution data which is not available in the most of organizations. For example, most individual-based accessibility models (e.g. Space Time) need to analyse fine geo-coded data such as high-resolution socio-demographic data, fine-grained geo-referenced census data or behavioural data of house holders, but there are strict restrictions worldwide on access to these data.

The second problem in data collection is related to inconsistency between the geographical zones in different sets of geo-coded data. For example, often the geographic boundaries of different data sets (e.g. census data, travel survey data) cannot match together, causing difficulty using various types of spatial data sets that have such different sets of geo-coded data.

The third problem refers to different survey time in data collection for different datasets. For example, some data sets are updated regularly every four years (e.g. travel survey data); other data sets are collected for specific requirements (e.g. subjective transport surveys). Also, in some cases, access to historical data may not be easy and it needs additional data cleaning process. This time interval inconsistency between different data sets can cause inaccuracy in the models, as the modeller may need to estimate and apply a weighting factor for converting these data.

The fourth limitation in data collection is that these data are usually not gathered subjectively for particular research projects and so may not contain all the required data that the modeller needs. For instance, estimating travellers' behaviour based on the household travel survey data may not be an adequate approach to observe travellers' route choice behaviour: the exposed path choice behaviour might not necessarily show the preferred behaviour. This issue is highlighted particularly when the passengers have no other option in the transport network.

The last limitation with collecting data is related to obtaining qualitative data for the modelling. Quantitative data can usually be obtained for the basic characteristics of land use and transportation systems, but finding and collecting qualitative data for a particular accessibility aspect is very rare. In this context, most of the accessibility literature acknowledged a significant gap between the qualitative data requirements and their availability in urban and transport planning departments (Cerdá, 2009; El-Geneidy & Levinson, 2006; Geurs & Van Wee, 2004; Handy & Clifton, 2001; Mesbah & Nassir, 2014).

Estimating the Travel Impedance

Reviewing the existing traditional accessibility models revealed that estimating travel impedance is one of the key issues in accessibility modelling. The existing accessibility models typically emphasised the impacts that are easy to measure at the cost of those that are not easy to estimate (Breheny, 1978).

On one hand, a number of accessibility models applied simple but misguided attributes for estimating the travel impedance; on the other hand, some models used complex attributes that are too difficult to measure (Lyborg, 2000).

For example, traditional accessibility models typically paid no attention to travellers' behaviour and the fine details of transit characteristics which are not easy to estimate; as a substitute they tried to explain the impedance of accessibility by simple travel time to opportunities. These approaches aimed to avoid complexities in the input (data collecting) and output (presenting the results) of the model.

Although some approaches aimed to improve the impedance estimations by incorporating other attributes into the model, some approaches are almost impractical in real-sized networks. For instance, space-time models which aimed to capture travellers' behaviour along with the transport restrictions and characteristics cannot be utilized practically for dense networks used by numerous travellers.

Weighting the Opportunities

Reviewing the accessibility models also revealed that results can be meaningfully affected by the choice of method adopted for calibrating the attractiveness of opportunities. In this regard, Guy (1983) compared the outcomes of accessibility measurements with different attractiveness factors for 'local' accessibility to shops and services. These measures not only resulted in different outcomes, but also confirmed that the accessibility level could be changed significantly when the model used different approaches for weighting the opportunities.

Although different approaches proposed weighting the opportunities, these concepts failed to capture the residents' sense and preferences in relation to the opportunities. These methods are not generally supported by a strong theoretical background and they cannot take quality of destinations into account. It is important to state that qualitative characteristics are highly subjective and are not easy to estimate in an accessibility measurement (Handy & Niemeier, 1997).

The accessibility models typically used only quantitative approaches for calibrating the attractiveness of destinations (e.g. number of employees in destination or number of available car parks). Although many researchers such as (Handy & Niemeier, 1997) suggested incorporating qualitative attributes (e.g. the quality and price of products) for weighting the opportunities, they did not suggest a firm solution for applying these features to the model.

Aggregating the output

Another drawback of the accessibility models relates to aggregating the models' outputs. Most accessibility models combined the accessibility results for different trip purposes or modes of travel without any robust theoretical approach. For example, accessibility measurements typically estimated the accessibility as a combined value of accessibility by different travel modes, even though various contributions may be provided by each mode of travel.

Ignoring Travellers' Choices and Preferences

Reviewing the accessibility modelling approaches also revealed that route choice techniques generally aimed to find a single shortest path (shortest travel time, distance or cost) between origin and destinations. These models assumed that travellers have all information about the network and transport system (e.g. transit timetables) and they could choose the best route among all available alternative routes. On the other hand, these deterministic accessibility approaches accepted that individuals can choose the alternatives associated with maximum utility to them, ignoring the freedom of travellers to choose other available routes in spite of great levels of inconsistency between travellers' preferences (Nassir, et al., 2014).

Measuring the accessibility models based on a shortest path approach instead of using multiple high-utility paths cannot provide a reliable accessibility measurement. First, different alternative routes are chosen by travellers at different times based on the route performance at any given time (e.g. minimum travel time or travellers' mode preferences at peak and off peak time). Second, most accessibility models assumed that travellers have complete understanding for all available alternative routes. However, a significant number of travellers choose non-optimal routes because they either do not have perfect knowledge of the network, or cannot distinguish the difference between alternatives. Third, considering the route alternatives allows consideration of unexpected changes in the network, such as natural disaster, temporary road maintenance or traffic congestions (Davidson, 2008; Nassir, et al., 2014).

As a result, existing deterministic accessibility approaches using a single shortest path cannot provide proper estimations for travellers' accessibility as they fail to capture travellers' path choice diversities and their indeterminacies in perceiving the transit network.

2.2.6 Transit accessibility approaches and models

Public transit is a key component of a transportation system as they improve mobility and accessibility while reducing car reliance (Lo, Tang, & Wang, 2008). Public transit is only part of a transportation system, improving this mode of travel is likely to benefit cities significantly (Murray, et al., 1998) and is critical for the comfort of households without an automobile and providing equal access for all the residence (Mavoa, et al., 2012). Public transit is becoming a preferred alternative, experiencing greater use by a wider socioeconomic range of people as a result of higher transport costs, environmental matters, and growing congestion in the cities (Tribby & Zandbergen, 2012).

Evaluating transit accessibility has attracted the particular attention of both policy makers and transport planners (Murray, et al., 1998), as they need to forecast the result of their decisions in the cities. However, as a result of various spatial and temporal dimensions of transit accessibility and its multimodal nature, finding a measurement to capture these varieties is not easy (Lee, 2009). Transit agencies and local governments have applied various measurements to assess different aspects of a transit system. These models reflect the various perspectives of their developers (Mamun, Lownes, Osleeb, & Bertolaccini, 2013) and can be used as a tool for the transportation and urban planners for comparing different development policies and justifying choices in public transit investment.

The first category of transit accessibility models dealt with physical access to public transit network, estimating how easy it is for a person to reach public transit stops by using different travel modes. These accessibility measurements, which are called system accessibility or access to transit stops, can only evaluate distance, time or effort to reach a transit network. In other words, these approaches can address the "first-mile" problem in the transit network. The second type of transit accessibility measurement is called system facilitated accessibility. Compared to the first category, system facilitated accessibility can measure a traveller's ability for reaching to opportunities by incorporating the travel time or cost spent in the transit network. The third type of transit accessibility measurement is called integral accessibility or access to destinations. While the first two types of measurement show access to a network or access provided by a transit facility to travel to a destination, the third group is associated with measuring overall access to a number of possible destinations and revealed how it is easy for a traveller to reach from an origin to opportunities via public transit (Lei & Church, 2010; Mavoa, et al., 2012).

For better understanding about the different transit accessibility model Figure 2-3 provide a schematic overview for these three approaches.

In the following section, a number of well-known methods of transit accessibility models in these three mentioned categories will be explained.

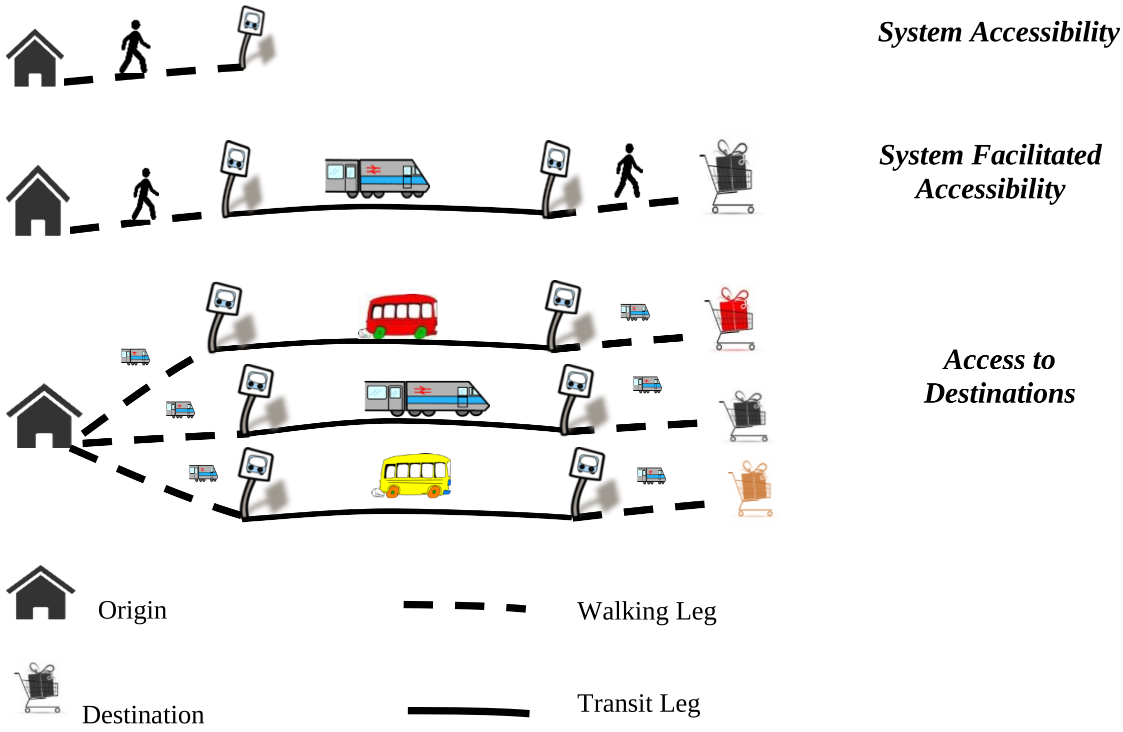


Figure 2-3: Schematic graph of different approaches for measuring transit accessibility

System Accessibility (Accessibility to Transit Stops)

Access to transit stops is important as reaching public transit is a main component of the public transit journey (Mavoa, et al., 2012). Various models for measuring the accessibility to transit stops were introduced by academics. Some suggesting a simple algorithm for measuring accessibility at this level, such as generating buffers around transit routes to identify the area served by the transit system (Lei & Church, 2010). In this context, Azar, Ferreira Jr, and Wiggins (1994) assumed that people who lived within a quarter-mile buffer of any transit link had acceptable accessibility. Some suggested incorporating the demographic data into the model: Gan (2005) proposed a tool called the FTGIS (Florida Transit Geographic Information System) to find the areas that are transit accessible by including the ratio of population served by the transit. A number of these models are described in this subsection.

Ideal and Actual Stop Accessibility Indices (ISAI and ASAI) and Stop Coverage Ratio Index (SCRI)

Foda and Osman (2010) introduced the ideal and actual stop accessibility indices (ISAI and ASAI) and the stop coverage ratio index (SCRI) for measuring accessibility to public transit stops. ISAI represents the accessibility to a bus stop through the nearby pedestrian road network and can be calculated by dividing the overall length of the pedestrian road network links located within a walking distance of 400 m by the ideal access coverage area of the bus stop, measured as a circle with a radius of 400 m (Figure 2-4). The higher the value of ISAI shown, the more connectivity the bus stop has to the network.

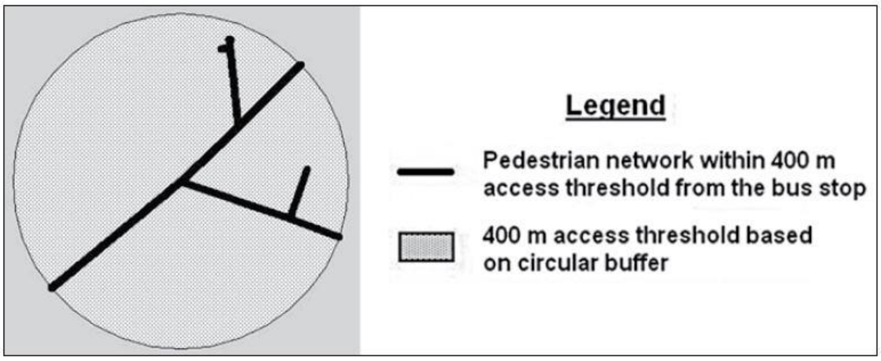


Figure 2-4: Ideal Stop-Accessibility Index or ISAI (Foda & Osman, 2010)

The ASAI can be calculated by dividing the overall length of the pedestrian road network links located within a walking distance of 400 m by the actual access coverage area of the bus stop measured on the basis of the geometric area of the pedestrian road network around the bus stop within the given walking distance (Figure 2-5). In ASAI the denominator is not a fixed rate like ISAI: it relates to the surrounding road network formation. However, in ASAI when an index value decrease still does not show whether the bus stop is less accessible or not, as this decrease may have occurred due to a greater bus stop access coverage area rather than being an effect of reducing the pedestrian road network length (Foda & Osman, 2010; Foda & Osman, 2008).

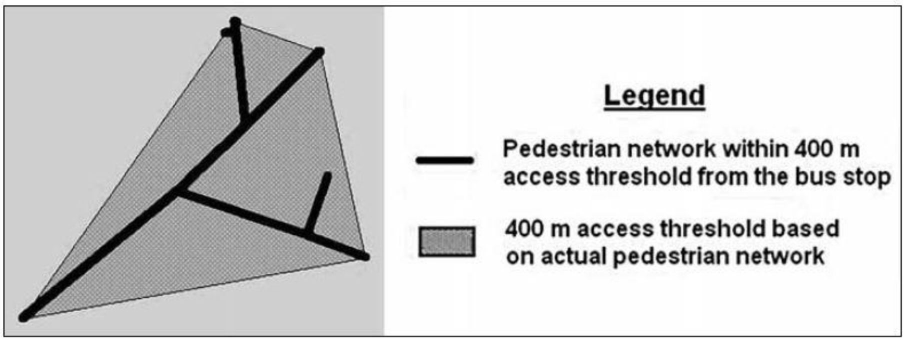


Figure 2-5: Actual Stop-Accessibility Index or ASAI (Foda & Osman, 2010)

The SCRI was also introduced by Foda and Osman (2010) to show the proportion of the actual access coverage to the ideal access coverage of a bus stop. This index can be calculated by dividing the actual access coverage area of the bus stop measured on the basis of the pedestrian road network paths (geometric area), by the ideal access coverage area measured as a circle with a radius of 400 m by assuming the bus stop is located in the centre of the circle (Figure 2-6).

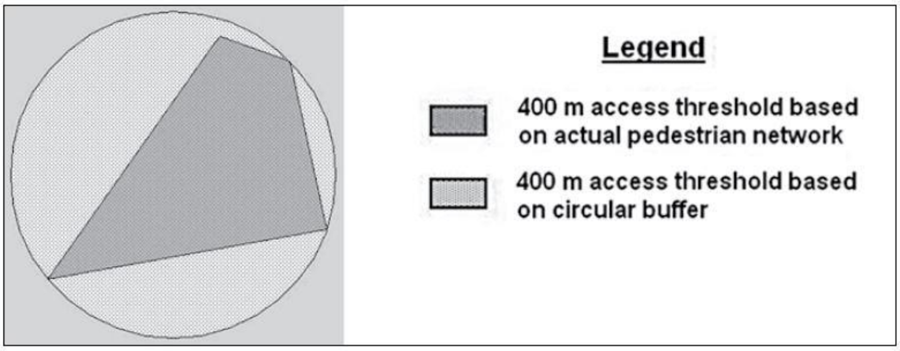


Figure 2-6: Stop Coverage Ratio Index or SCRI (Foda & Osman, 2010)

As seen in these models, researchers have typically used conventional walking distances for estimating the access to transit stops. For instance, a 400 m (0.25 mile) distance was generally adopted as accepted walking distance to transit stops (Azar, et al., 1994; El-Geneidy, et al., 2010; Foda & Osman, 2010; Mavoa, et al., 2012). However, using these fixed values for different case studies can be a strong assumption: in most cases the average access and egress distances are generally different to the adopted distance (400 m) in these techniques. Based on an analysis of the Household Travel Survey (HTS-2009) in SEQ (South East Queensland) for the transit trips with walking elements at both end, the median distance that people walk from origin to public transit stops (access travel leg) is 628 m and for walking from public transport stops to opportunities (egress travel leg) is 624 m.

These accessibility indices presented only an overview of accessibility to public transport stops; they do not consider public transport quality and travellers' behaviour. There is no doubt that modelling the accessibility to transit stops, based on a geographic distance and without including the difficulties a person may experience in travelling to public transit, cannot provide an accurate estimation for modelling the accessibility to transit.

To improve the accuracy of system accessibility estimations, Polzin, et al. (2002) developed another platform to estimate access to a transit by incorporating the spatial (e.g. spatial distribution of population and employment) and temporal dimensions (e.g. temporary service availability), along with transit schedule times. Although the proposed model expanded the definition of physical access by including the temporal aspects (e.g. time of day) the model again simplified the access distance calculation, proposing a half-mile buffer zone around a transit route to calculate the service area and also defining a fixed waiting time (10 min) for all services to calculate the temporal service availability.

Public Transport Accessibility Levels (PTALs)

PTAL (Public transport accessibility level) is one of the well-known distance-based system accessibility models which used in UK since 1992. The PTALs also incorporated public transport attributes by applying an average waiting time based on the frequency of services, the reliability factor. Walk times are calculated from origins to all public transit stops located within pre-defined catchment areas. Total access times in this model needs to be converted to an EDF (Equivalent Doorstep Frequency) factor for each destination; the EDF values are then summed up for all routes within the catchment area and for the different modes (bus, rail, etc), to incorporate the benefits offered by the different routes (Kerrigan & Bull, 1992; Wu & Hine, 2003). EDF for each possible route is calculated by below equation:

$$\text{EDF} = 30/\text{Access Time (minutes)} \qquad (2\text{-}22)$$

For calculating the Accessibility Index (AI) for a single mode in this model, all EDFs for all available routes need to sum up with a weighting factor in favour of the route with maximum EDF value.

$$AI_{\mathrm{mod}\,e} = \text{EDF max} + (0.5 * \text{All other EDFs}) \qquad (2\text{-}23)$$

Overall accessibility index then can be calculated as the total of the individual accessibility indices for all modes:

$$AI_i = \sum_{\mathrm{mod}\,e=1}^{n} AI_{\mathrm{mod}\,e} \qquad (2\text{-}24)$$

Although the PTALs model has an advantage to include the choice of routes and transit modes, it did not aim to incorporate socio-economic aspects of transit accessibility and travellers' behaviour into the measurement. Also, defining walking catchment area in this model for different transit modes are not based on a strong theoretical approach and the model only suggested applying pre-defined travel times (e.g. 8min for bus stop, 12min for light rail stop).

Transit Score

Analysts and researchers in the fields of urban planning, public health, and finance (WalkScore, 2015) also developed a system accessibility measure in the context of gravity-based approach known as "Transit Score". A raw transit score is calculated as overall value of all nearby routes. The value of a route is defined as the service level (frequency per week) multiplied by the mode weight (heavy/light rail is weighted 2X, ferry/cable car/other are 1.5X, and bus is 1X) multiplied by a distance penalty. This distance penalty to transit system estimates the distance to the nearest stop on a route and then uses the distance decay function for scoring the walk to the nearest stop. While any measure of transit infrastructure (e.g. number of stops, number of weekly trips) will have its own unique range, the raw transit score is normalized to generate a transit score from 0 to 100.

This model has several major shortcomings as it used arbitrary approach for weighting the transit modes and also distance decay function.

Environmental Transit Accessibility Index (ETAI)

(Rastogi & Rao, 2002, 2003) introduced and developed a utility-based accessibility model, considering random utility for access to transit stations, using socioeconomic variables, mode availability (e.g. walk, bicycle and bus), impedance for access to the station on each mode, and the environmental impacts of each mode.

The proposed model, known as the environmental transit accessibility index (ETAI), accounted for the effect of the socioeconomic characteristics of travellers, the environmental effects and transport attributes for modelling the accessibility to transit stops. In this model, choice of access mode for accessing the transit station should be determined by the socioeconomic characteristics of the individuals, the impedance for access to the station on each mode, and the environmental impacts of each mode in a random utility framework. The ETAI is defined as a functional form of mode availability factor (M_{af}), detour factor (D_f), access environment condition index (

C_i), shift potential and environmental saving (S_p) and environmental saving (E_s). ETAI under policy effects can be defined as (Rastogi & Rao, 2002, 2003):

$$ETAI_{policy} = (M_{af} + D_f + C_i + S_p)\exp(E_s / E_{ms}) \qquad (2\text{-}25)$$

where:

E_{ms} maximum possible environmental savings.

The simplified flowchart of ETAI is presented in the Figure 2-7.

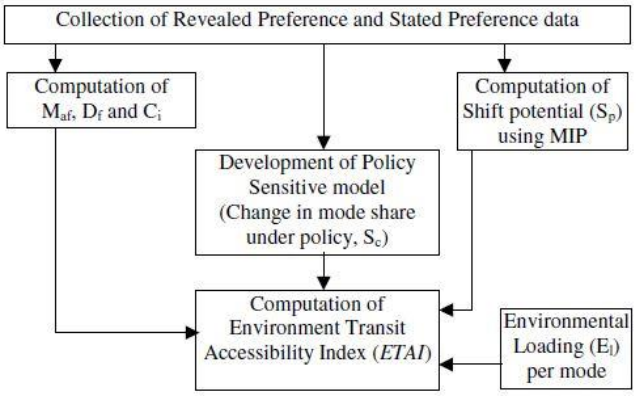


Figure 2-7: ETAI Computation Flowchart (Rastogi and Krishna Rao, 2003)

The mode availability factor (M_{af}) is defined as a function of access modes availability and their distance.

$$M_{af} = [(N_{ma} / N_{tm}) + (A_v - A_d)/(A_v)]*100 \;\; ; 200 > M_{af} > -100 \text{ (for } A_d \approx 2A_v) \qquad (2\text{-}26)$$

where

N_{ma} maximum number of access modes

N_{tm} number of modes available to traveller

A_d distance to available transit service stop

A_v average distance to transit service stops

The detour factor (D_f) is taken as a function of the detour distance (D_d) and aerial direct distance (D_a) of travellers to the transit station.

$$D_f = -[(D_d - D_a)/D_a]*100 \text{ where } 0 > D_f > -100 \quad (\text{for } D_d \approx 2D_a) \quad (2\text{-}27)$$

The condition index (C_i) is defined as weighted sum of walkway condition (S_w), type of bus stop (B_s) and condition of access road surface (R_a).

$$C_i = [S_w + B_s + R_a]/3 \text{ where } 100 > C_i > 0 \quad (2\text{-}28)$$

The shift potential is defined as a function of system attributes along with socioeconomic characteristics of travellers and is computed based on maximum information algorithm (MIP). Motivation to shift is posed only to travellers who are not accessing the transit station by walk or bicycle. The information provided primarily related to the better walk/bicycle facility, the environment soundness comparison of the modes, the limitations of the use of walk/bicycle, and the improved walk/bicycle facility scenario, before finally calculating the subjective willingness of the traveller to shift (Rastogi & Rao, 2002, 2003). Figure 2-8 shows the proposed algorithm for computing the shift potential.

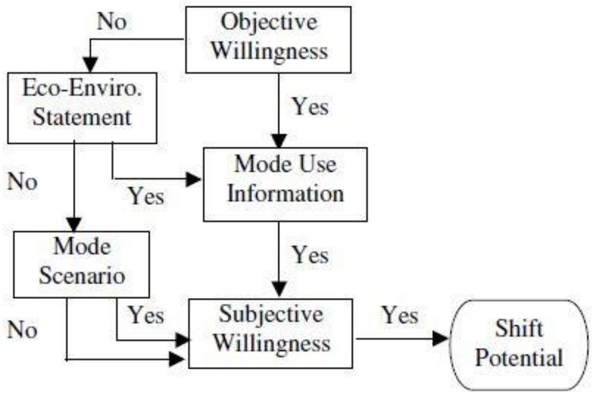


Figure 2-8: Maximum information procedure for computing the shift potential (Rastogi and Krishna Rao, 2003)

The ETAI model can be utilized for exploring the effect of transport policies in the planning stage and in post-implementation period; it can also work as a tool for the transportation and land-use planners for examining different policies and development scenarios (Rastogi & Rao, 2003). The model incorporates the choice of access mode and aggregated data of choice of access stops (average distance to transit service stops) into the model. Although the model aims to consider random utility for access to transit stations, it did not use strong theoretical bases for estimating the impedance attributes. The model cannot capture either the travellers' behaviour or stochasticity in perceptions of transit impedance to actual (final) destinations.

System facilitated accessibility

Many researchers including Lei and Church (2010) and Mavoa, et al. (2012) acknowledged that it is important not only to focus on accessibility to transit stops, but to find accessible areas by travelling on public transit.

Reviewing system facilitated models shows that although these measurements mainly used distance-based approaches for estimating the accessibility, they utilised different methods for estimating the distance in the transit system. Liu and Zhu (2004) developed a GIS tool called ACCESS to estimate the system facilitated accessibility. This model used cumulative platform for measuring the transit accessibility by measuring number of residents have access to a particular destination within specified time or cost. The proposed model has examined in the Chao Chu Kang-Bukit Panjiang area, Singapore and it calculated the shortest travel times from origins to a destination by using the distance and average travelling speed in each part of the trip (access, in-vehicle and egress). The model also estimated the trip cost and covert it to travel time for calculating the travel impedance. Although, this model structured based on a shortest network distance algorithm, it does not consider the waiting time and the frequency of transit system.

More complex measurements in the context of system facilitated approach incorporated attributes such as transfer time, wait time and detailed schedule information. For example, Hillman and Pool (1997) introduced a GIS-based tool, ACCMAP, to incorporate the walk time to a stop, the waiting time at the stop , the in-vehicle travelling time and also frequency of transit services in peak and off-peak time. The model can be also integrated with land-use and census data to highlight low-serviced location for specific population groups.

Tribby and Zandbergen (2012) also proposed a high-resolution, multimodal model that used total travel time as the accessibility measurement. The model, developed in ArcGIS, considers the walking time from residential locations to a bus stop, the waiting time at a bus stop, the travel time on the bus, and any necessary transfers. Travel times were estimated with an origin-destination analysis in the network analyst extension. The network was combined with the temporal attributes of the morning peak, afternoon peak, and off-peak bus travel times and waiting times. They also aggregated socio-economic data (e.g. low income group, car-less, older than 65) to identify the poor transit accessibility area.

Access to Destinations

Measuring the access to various activities opportunities is the ultimate goal in the accessibility models. As explained in the system facilitated accessibility models, these approaches show the accessible area via public transit, but they do not aim to consider the importance of destinations. This third category of measurement estimated overall access associated with a number of possible destinations. Several methods have been proposed to measure this overall transit accessibility between origin and destination.

Alam, Thompson, and Brown (2010) developed a gravity model for predicting transit accessibility that incorporated travellers' preferences, the attraction of destinations, and the cost of travel. The general formula, shown in equation (2-29), estimated transit flow between two zones as a product of the variables producing transit trips in the origin zone, the variables attracting transit trips in the destination zone, and the variables describing friction between two zones.

$$T_{ij} = (PDN_i^p) * (ATN_j^a) * (F_{ij}^f) \qquad (2\text{-}29)$$

where:

T_{ij} transit trips between zone ***i*** and ***j***

PDN_i vector of transit trip production variables and their estimated parameters in zone i

ATN_j vector of transit trip attraction variables and their parameters in zone j

F_{ij} vector of friction variables and their parameters that travellers encounter when travelling between i and j

p, a and f vectors of parameters to be estimated

Hence, the accessibility index can be generated from this equation by summing the equation over all zones in the region:

$$\sum_{i=1}^{n} T_{ij} = P_i = (PDN_i^p) * \sum_{i=1}^{n} \left[(ATN_j^a) * (F_{ij}^f) \right] \qquad (2\text{-}30)$$

This equation stated that transit trips produced in zone i ,denoted as P_i , are the potential for zone i to generate trips ,denoted as (PDN_i^p), multiplied by the transit accessibility of zone i to all destinations in the region. As a result, the transit accessibility is shown as (Alam, et al., 2010):

$$TA_{ij} = \sum_{i=1}^{n} \left[(ATN_j^a) * (F_{ij}^f) \right] \qquad (2\text{-}31)$$

Similar to other gravity-based models, this approach has difficulties in calibrating the decay functions (friction variables) and weighting the opportunities, due to the inherent complexity of gravity models previously discussed.

(Bhat, et al., 1999; Bhat, et al., 1998) introduced and developed a “parallel conductance” calculation as an alternative logsum technique. This method measure the perceived travel utility by the combination of travel mode choices (auto, transit, and walk) to different destinations. In-vehicle-time, out-of-vehicle-time, and cost of all three modes were estimated as utility attributes for modelling the destination choice in this technique. They used also travel survey data from Boston, MA for destination choice modelling. The main model limitation in this technique is that the composite utility of each mode was estimated deterministically and it was represented as based on the utility of the path with the highest systematic utility. As a result, the model cannot capture the travellers’ preferences and their stochasticity in perceptions of transit network.

Public Transit and Walking Accessibility Index (PTWAI)

Mavoa, et al. (2012) developed the public transit and walking accessibility index (PTWAI), which measured the potential access between land parcels and opportunities via public transit (buses, trains and ferries) and walking modes. The PTWAI, based on travel time, included the service level/frequency of public transport. Although PTWAI aimed to provide a high resolution accessibility measurement, it adopted a fixed 10 min waiting time for all transit stops and ignored travellers’ behaviour and preferences in the proposed model.

Land Use and Public Transport Accessibility Indexing Model (LUPTAI)

Another model in this category is LUPTAI (the Land Use and Public Transport Accessibility Indexing Model), an origin-based model which estimated the transit accessibility via walking and the public transport (PT) network. The LUPTAI modelling process contains three main steps: (a) estimating walking accessibility based on walking distances to/from public transit stops; (b) estimating PT accessibility based on PT travel time; and (c) combining both measures and assigning accessibility index values to each defined grid cell. The composite index assumed that each of opportunities (i.e. education, health, shopping) is weighted equally (Yigitcanlar, et al., 2007). The LUPTAI is based the on Geographical Information System (GIS), which makes the calculations simple, but it requires an extensive set of data for processing (Davidson, 2008).

Although LUPTAI is a decision support tool that enables local and state governments to optimise land use and transport integration (Pitot, Yigitcanlar, Sipe, & Evans, 2006), it has some limitations. The major limitation of the model is related to defining conventional cut-off distances for walking (i.e. 400, 600, 800, 1,000 and 1,200 m) to evaluate the quality of access to transit stops.

To treat this limitation, newer versions of the model have suggested applying a utility destination choice model to estimate the accessibility. A review of this upgraded version of LUPTAI model (Davidson, 2008) revealed that the random-utility model applied only to the destination part of the accessibility model, while the impedance part of the model is estimated deterministically based on the generalised cost of the shortest path to different destinations. As a result, the model could not capture travellers' preferences and their subjectivity in the perception of transit network.

As mentioned in the review of accessibility models, one of the drawbacks to the existing models is related to ignoring travellers' choice and preferences in the transport network. To treat this limitation in the accessibility models, the concept behind the route choice and route set generation approaches need to be clarified in the first step. In the following section, the approach of route choice and the common route choice techniques will be discussed in brief.

2.3 ROUTE CHOICE MODELLING

Decision-making models in transport are often discussed as a difficult practice as they have to model and analysis the choice behaviour in large transportation networks (Frejinger, 2008). Among these decision-making models, route choice models have an important role in every transport system as they need to find most probable routes which travellers may take to go to a destination.

As most of the existing route choice models employed discrete choice frameworks in their methodology, it is important to discuss discrete choice models before giving an explanation about route choice modelling.

2.3.1 Discrete choice approach

Discrete choice models, developed mainly during the last 50 years, have been applied by researchers in a variety of disciplines. The primary transportation applications of discrete choice models have been introduced for travel mode choice. However, these models have been applied in different transport areas such as destination choice (Bhat, 1998; Train, 1998) and route choice (Cascetta, Russo, Viola, & Vitetta, 2002; Yai, Iwakura, & Morichi, 1997).

These models can be used to examine and estimate decision maker preference in choosing an alternative from a limited set of mutually exclusive choices. As a result, the final goal in discrete choice modelling is to estimate the individual preferences (Koppelman & Bhat, 2006). In these models, a decision maker needs to find the choice with the highest utility among the available alternatives at the time a choice is made (Ben-Akiva & Lerman, 1985). These models have four main components.

The first element, decision-makers, can be people, driver and organisation. The second aspect is the available choices or alternatives (e.g. different products, routes and destinations). To be acceptable within a discrete choice framework, these choice sets need to have three characteristics. First, the choice set must be mutually independent: choosing one alternative necessarily indicates not choosing any of the other alternatives. Second, the choice set must be comprehensive, to include all possible alternatives. Third, the number of choices must be limited (Koppelman & Bhat, 2006; Train, 2009).

The third component of discrete choice models is the attributes of alternatives. The alternatives or choices in a choice model should be determined by a set of attribute values. The attributes of choices can be identical for all alternatives or they can be choice-specific for different alternatives.

Having a decision rule is the fourth element of the discrete choice model. A decision maker uses a decision rule, a method to evaluate the choices and to choose an alternative among a choice set. This decision rule can be random choice, variety seeking, or illogical (Koppelman & Bhat, 2006).

Generally, the random utility model (RUM) is a decision rule for discrete choice models when individuals obtain the utility from their alternatives. The decision rule can be translated as a function of the individuals' characteristics and the attributes of alternatives to estimate an individual's utility for each choice (Koppelman & Bhat, 2006). The basic assumption in random utility models is based on the concept that decision makers aim to maximise the utility by choosing the high utility alternatives. As presented in the following equation, an individual chooses alternative i to obtain the highest utility among all the alternatives in the individual's choice set, C (Train, 2009). This can be expressed mathematically as:

$$U_{ni} > U_{nj} \forall j \neq i \qquad \text{(2-32)}$$

Since we cannot observe the individual's utility entirely, or individuals may choose their choices without any visible reasons, the utility evaluation cannot be a simple process. The observed attributes of the alternatives can be presented as:

$$V_{ni} = V(x_{ni}) \forall i \qquad \text{(2-33)}$$

We can call V_{ni} a deterministic or systematic component of the utility model. Since there are characteristics of utility that we cannot observe, $V_{ni} \neq U_{ni}$. There are three main sources of miscalculation in the use of deterministic utility functions. First, the individuals may not have complete or accurate information or may make an error about the effect of the attributes. Second, the observer has different or incomplete information about the influence of various attributes on individuals and therefore cannot evaluate the utility of each alternative accurately. Third, the observer cannot consider each individual's particular conditions in their decision making. Therefore, the utility function can be defined as $U_{ni} = V_{ni} + \varepsilon_{ni}$ where ε_{ni} captures the random factors or stochastic components which cannot be determined and are not observable by the researcher (Koppelman & Bhat, 2006; Train, 2009). Theoretically, error terms are unseen and cannot be measured accurately. Thus, for modelling the error term, we need to assign an appropriate probability model to the random component (Train, 2009).

The utility formulation can rewrite the probability that individual *n* chooses alternative *i* as (Ben-Akiva & Lerman, 1985):

$$\begin{aligned} P_{ni} &= \Pr(U_{ni} > U_{nj} \forall j \neq i) \\ &= \Pr(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \forall j \neq i) \\ &= \Pr(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \forall j \neq i) \end{aligned} \qquad (2\text{-}34)$$

As by using the density $f(\varepsilon_n)$, this probability is a cumulative distribution and can be written:

$$P_{ni} = \int_{\varepsilon} I(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}) f(\varepsilon_n) d\varepsilon_n \qquad (2\text{-}35)$$

Where $I(0)$ is an indicator function, equal to 1 when the expression in parentheses is true and otherwise it is 0. Therefore, this is a multidimensional integral over the density of the unobserved portion of utility, $f(\varepsilon_n)$. Various distribution models, such as the multinominal logit model (MNL) and the nested logit model (NL) have been proposed to represent this error terms over individuals and their choices. Before discussing these proposed models for calculating the stochastic part in the route choice modeling, it is important to discuss on the route set generation models.

Generally, route choice modeling can be divided into a two-step process. First, the possible alternative routes need to be generated from the choice set. Second, the probability that a given route is chosen from an identified choice set needs to be calculated (Bekhor, Ben-Akiva, & Ramming, 2006). Hence, all route choice models require choice sets, which can be generated by a route set generation approach. Some of these well-known approaches will be explained in the next section.

2.3.2 Route set generation

A route set generation model should generate the routes which travellers may choose in their journey. Choosing the right routes is very important as the routes outside the route choice set can never be employed by route choice models. However, the choice set necessarily cannot cover all available routes (Telgen, 2010). In realistic networks, the number of alternative routes should be a very large number, but people may use only a few attractive paths (Ramming, 2002).

Generally, route set generation approaches can be divided into two types of theories: deterministic approaches and stochastic approaches. The basic assumption in deterministic choice set generation methods is that travellers have complete knowledge about the routes and their associated costs in the network (Telgen, 2010). In this approach, the optimal paths compute based on repeated shortest path searches and adjustment of one or more search terms such as link impedances or route variables in the network (Prato, 2009).

The stochastic approach is based on iterating shortest path searches in the network, while these models apply a random extraction of route impedances or travellers' tastes from probability distributions for finding the best possible routes. This approach defines a correction term representing the unequal probabilities of alternative routes (Bovy, Bekhor, & Prato, 2009; Frejinger, 2007; Frejinger, Bierlaire, & Ben-Akiva, 2009; Prato, 2009). Approaches such as the shortest path, labelling, path size penalty algorithm, link elimination and link penalty can be clustered as deterministic approaches; simulation, doubly stochastic generation, constrained enumeration and probabilistic approaches can be grouped as stochastic approaches for choice set generation. In the following, these well-known route set generation approaches are explained in brief.

Shortest Path Approach

Most route set generation models in the context of deterministic approaches are based on the shortest path method. In this approach, it is assumed that travellers try to minimize a trip attribute or a mix of travel attributes (e.g. travel time or distance) to maximise their utility for reaching a destination. Thus, the basic assumption in this model is that travellers have knowledge to choose a shortest path or a route which maximises their utility (Telgen, 2010).

The behavioural theory behind the search for K shortest paths is that travellers choose their alternatives to minimise the cost of travel. The number of generated paths shows the acceptable costs between either the shortest path or the path with maximum utility and the K-th shortest path. The major drawback of the K-shortest path technique is that this method generates extremely identical routes in the network (Prato, 2009).

Labelling Approach

The basic assumption in the labelling approach is that different travellers have different tastes and they aim to minimize attributes associated with their preferences, such as travel time, cost, traffic lights or safety. Each of these preferences may define different route choices, and therefore, each choice can be labelled based on the different criterion for which it is the optimum (Prato, 2009; Ramming, 2002).

The main drawback of the labelling approaches is that they can create only part of the travellers' actual choices, and so the accuracy of the generated route choice sets in this approach depends on the definition of the labels (Prato, 2009).

Link Elimination Approach

The link elimination approach is based on iterative searching that identifies the shortest path, removes part or all of the shortest path links distinguished from the previous iteration, and then searches for the new shortest paths or links (Ramming, 2002).

Although this approach generated different alternative routes, it has a major drawback in that it eliminates one or all of the links on the shortest path at once or removes major crossing routes. This limitation may make this method unsuitable to create distinct paths between origin and destination (Prato, 2009).

Link Penalty Approach

The link penalty approach is also based on the repetitive examination for finding the shortest path. In this method, a penalty term is defined as an impedance for all links used by the previously-identified shortest paths (Ramming, 2002). As a result, this method is prevented from choosing the same set of links. It generated routes which were not identical to previously chosen paths as the amount of penalty was changed in each iteration.

The link penalty approach has the advantage of identifying extremely dissimilar routes in each iteration, but the success of this method greatly depends on the penalty factor definition. Defining the penalty values in this approach is very critical: low values for the penalty can create similar paths, while by choosing high values for the penalty, the model generates unattractive paths in place of actual attractive routes (Prato, 2009).

Path Size Penalty Algorithm

The path size penalty algorithm (PSPA) belongs to the category of iterative penalty-based Kth shortest path algorithms. The main change between PSPA and other penalty-based algorithms is that in the PSPA, the proposed penalty values are applied to the link costs before every iteration. This penalty term shows the value of path overlaps between the paths already generated (Nassir, et al., 2014).

The proposed penalty term in this algorithm is defined based on the Path Size Correction (PSC) factor suggested by Bovy et al. (2008). PSC_i is the Path Size correction factor which considers the path overlaps between the links of path i and the other paths in the choice set. PSC_i can be calculated for each path as (Nassir, et al., 2014):

$$PSC_i = -\frac{1}{\mu}\sum_{a\in\Gamma_i}\frac{l_a}{L_i}\ln\sum_{j\in C_n}\delta_{aj} \qquad \text{(2-36)}$$

where:

Γ_i : Set of all links in the path i,

C_n : Set of paths between origin and destination considered by an individual, n.

l_a : Length of link a,

L_i : Length of path i,

δ_{aj} : Link-path incidence factor (equals 1 if link a is in path j and 0 otherwise),

μ : Scale factor (equals 1 in this research),

V_i : for each link in the network can be estimated from the former section.

The PSPA algorithm is based on applying the overlaps in the paths generated in previous iterations, and is not based on the final set of paths (Nassir, et al., 2014). This method has an advantage, compared with other route set generation approaches, as assigning the penalty term with this proposed algorithm allows the generation of more dissimilar paths in a route set generation. However, again similar to other penalty-based approaches, generating the attractive paths is highly dependent on choosing a proper penalty factor.

Simulation Approach

The idea of the simulation approach originates from the Multinomial Probit (MNP) model for traffic assignment and developed by Sheffi and Powell (1982) for applying a Probit model. The behavioural assumption of this approach is that travellers identify path costs with miscalculation. This error term can be represented by generalized cost functions from probability distributions. The advantage of the method is to generate a large number of attractive routes by selection of an appropriate probability distribution. However, finding a proper probability distribution value for the cost function is the main challenge in this method (Prato, 2009; Sheffi & Powell, 1982).

Doubly Stochastic Generation Method

The doubly stochastic generation method was developed by Bovy and Fiorenzo-Catalano (2007) to include the link attributes and the generalized cost for every shortest path search. The basic hypothesis of this approach is that the size and characteristic of the choice set is highly related to travellers' preferences. The doubly stochastic generation method relies on the behavioural assumption that travellers not only find path costs with error, but also have different judgments and opinions regarding the route choice (Bovy & Fiorenzo-Catalano, 2007; Prato, 2009).

The main benefit of this method is related to the high relationship between the generated routes and the actual routes chosen. However, the model cannot generate diverse routes for all the conditions in a real network (Nassir, et al., 2014). This model also has a shortcoming with choosing the optimum probability distributions, with an additional complexity in distribution of the value-of-time (Bovy & Fiorenzo-Catalano, 2007; Prato, 2009).

Constrained Enumeration Methods

The primary assumption of constrained enumeration methods is that travellers choose the routes according to their behavioural patterns rather than finding the paths to minimize their cost (Prato, 2009).

Constrained enumeration methods produced a comprehensive choice set that extremely is valuable for utility parameter estimation. However, the nature of the method provides all attractive routes with some unattractive paths (Bovy, 2009). The main criticism of the method relates to the definition of the thresholds for the behavioural constants (Prato, 2009).

Probabilistic method

The probabilistic method is one of the stochastic route set generation models, in which a generated probability is assigned to each route (Prato, 2009). Researchers developed different types of probabilistic methods including Choice Set Indicators (Ben-Akiva & Boccara, 1995), the Availability Perception model (Cascetta & Papola, 2001) and the Random Walk (Frejinger, 2007).

Each of these proposed models suggests a different algorithm for calculating and assigning the probability to the routes. For instance, the random walk considered a probability for each link according to its distance from the shortest path and applied it based on a generalized cost function. These methods have a limitation in calculating and assigning the probabilities to all the links in a real network (Frejinger, 2007; Frejinger, et al., 2009; Prato, 2009).

As stated earlier, the next step in the route choice algorithm is to find the probability that a given route can be chosen from a specified route choice set. These techniques are known as route choice models. The following section provides a brief review on these route choice models.

2.3.3 A review of route choice models

Route choice models, predict the path choice of a given traveller when going from a given origin to a destination. As discussed in the previous section, various route choice models were introduced, based on how the model defined the random part of the utility model. In the following, six of these popular models are explained.

Multinomial Logit Model (MNL)

The multinomial logit model (MNL) is the most popular choice model, due to its simple mathematical structure and simplicity of estimation. As stated in the discrete choice approach, a traveller chooses his/her route from the choice set based on the utility value U_{ni}; as an observer cannot have total information about the travellers' preferences, this utility value can be defined by a deterministic part V_{ni} and a random part ε_{ni} (Telgen, 2010).

This approach is based on three assumptions: first, the error term is described by the exponential Gumbel distribution; second, the error terms should be distributed independently for all alternatives (Independency of Irrelevant Alternatives); third, the error term should be distributed independently among all observations (Koppelman & Bhat, 2006). The Independency of Irrelevant Alternatives (IIA) will be discussed in the following section. The probability for choice i from choice set C_n in this method can be expressed by a function of the systematic portion of the utility of all the choices (Ben-Akiva & Lerman, 1985; Koppelman & Bhat, 2006):

$$P_i = \frac{\exp(\mu V_{ni})}{\sum_{j \in C_n} \exp(\mu V_{nj})} \qquad (2\text{-}37)$$

Where μ is a scale parameter and V_{ni} is utility of route i. The utility of the route is usually expressed by the negative travel time. The exponential in the probability distribution guarantees that changes in travel times can significantly affect the route choice probabilities (Telgen, 2010). The main limitations of MNL models can be summarised: first, it is assumed that variables are independent; second the model assumes that all individuals have similar perceptions; third, the model does not take route overlapping into account (Ben-Akiva & Lerman, 1985; Prato, 2009; Telgen, 2010).

Independence of Irrelevant Alternatives Property

As discussed above in the multinomial logit models, it is assumed that the alternatives need to be independent in the model. The independency of irrelevant alternatives or IIA property explained that the probabilities of choosing between two choices or alternatives are independent of attributes of any other alternative (Koppelman & Bhat, 2006).

In other words, choosing an alternative in a choice set is not relevant to the decision of choosing of other alternatives. The IIA assumption in MNL models has several advantages. First, it allows adding or removing the choices/alternatives from the choice set without affecting the structure or the model's attributes. The model can be applied when different individuals have different sets of alternatives. Second, this independency makes the MNL model estimation easier. Third, this will be helpful when applying the model for choice probabilities estimation for new choices/alternatives (Koppelman & Bhat, 2006).

C-Logit

The C-Logit model was introduced by Cascetta et al. (1996) to overcome the path overlapping problem with MNL models. In this model, a commonality factor is defined to show the degree of similarity of each route to the other routes in the choice set C. The probability of choosing route i within the choice set C can be expressed by (Cascetta, 2001; Cascetta, Nuzzolo, Russo, & Vitetta, 1996):

$$P_i = \frac{\exp(V_i + \beta_{CF} \times CF_i)}{\sum_{l \in C} \exp(V_l + \beta_{CF} \times CF_l)} \qquad (2\text{-}38)$$

where:

V_i , V_l the utility functions of route i and l, respectively,

CF_i , CF_l the commonality factors,

β_{CF} correction factor coefficient (to be estimated).

The commonality coefficient can be defined as (Cascetta, et al., 1996); (Cascetta, 2001):

$$CF_i = \ln \sum_{l \in C} \left(\frac{L_{il}}{\sqrt{L_i L_l}} \right)^{\gamma_{CF}} \quad (2\text{-}39)$$

$$CF_i = \ln \sum_{a \in \Gamma_i} \left(\frac{L_a}{L_i} \sum_{l \in C} \delta_{al} \right) \quad (2\text{-}40)$$

$$CF_i = \sum_{a \in \Gamma_i} \left(\frac{L_a}{L_i} \ln \sum_{l \in C} \delta_{al} \right) \quad (2\text{-}41)$$

where:

L_i , L_l the length of routes i and l, respectively,

L_a the length of link a,

Γ_i the set of links belonging to route i and,

δ_{al} the link-path incidence dummy, equal to one if route i uses links a and zero otherwise.

The main benefit of the C-Logit model is that the utility parameter is estimated with regard to the choice set size (Prato & Bekhor, 2007). The limitation of the C-Logit model is that the defined commonality coefficient shows only part of the similarity and there is no established framework to choose the appropriate equation for commonality factor estimation (Prato, 2009).

Path Size Logit

Path-Size Logit (PSL) model was introduced by Ben-Akiva and Bierlaire (1999) and developed by Ramming (2002) to overcome the shortcoming of MNL models in regard to overlapping. The PSL model defined a size variable in the utility of a path. They proposed the following equations for calculating the path size coefficient:

$$PS_i = \sum_{a \in \Gamma_i} \frac{L_a}{L_i} \frac{1}{\sum_{l \in C} \left(\frac{L_i}{L_l} \right)^{\gamma_{PS}} \delta_{al}} \quad (2\text{-}42)$$

$$PS_i = \sum_{a \in \Gamma_i} \frac{L_a}{L_i} \frac{1}{\sum_{l \in C} \delta_{al}} \quad (2\text{-}43)$$

where

L_i , L_l the length of routes i and l, respectively,

L_a the length of link a,

Γ_i the set of links belonging to route i and δ_{al} is the link-path incidence dummy,

γ_{PS} the weighting parameter

Therefore, the probability of choosing route i between alternative paths can be described as:

$$P_i = \frac{\exp(V_i + \beta_{PS} \times \ln PS_i)}{\sum_{l \in C} \exp(V_l + \beta_{PS} \times \ln PS_l)} \quad (2\text{-}44)$$

where

PS_i, PS_l the path sizes of routes i and l, respectively,

β_{PS} the path size coefficient (to be estimated).

Although C-Logit and PSL models have similar functional forms, each model provides a different explanation regarding the correction coefficient in the utility function. The first part of the path size equation (Eq.2-42) explains the impedance weight of link overlapping as the ratio between link and route lengths. The second part of the equation, which shows the number of paths using a specific link, is equal to one for links used by only one path. Therefore, the proposed formulation can estimate different level of contributions for the routes with different lengths (Ben-Akiva & Bierlaire, 1999; Prato, 2009).

On the other hand, the proposed path size equation by Ramming (2002) (Eq 2-43) could reduce the effect of very long paths on the utility of other paths in the choice set.

The main drawback of PSL models relates to high computational efforts for path size parameter estimation. Another drawback is that the path size model considers only part of the correlation between the alternatives (Prato, 2009; Prato & Bekhor, 2007; Ramming, 2002).

Path Size Correction Logit

The path size correction logit (PSCL) model was proposed by Bovy, Bekhor, and Prato (2008) to include the random utility theory into the path size factor. They proposed a new path size factor different from the original path size factor to overcome the well-known limitation of the C-logit and PSL models in correction factor estimations. In the PSCL models the probability of choosing route k within the alternative paths can be explained by the following equation (Bovy, et al., 2008):

$$P_k = \frac{\exp(V_k + \beta_{PSC} \times \ln PSC_k)}{\sum_{l \in C} \exp(V_l + \beta_{PSC} \times \ln PSC_l)} \qquad (2\text{-}45)$$

where

PSC_k, PSC_l the path size corrections of routes k and l, respectively,

V_i , V_l the utility functions of route i and l, respectively,

β_{PSC} the path size correction coefficient (to be estimated).

The path size correction factor can be described similar to path size coefficient as:

$$PSC_k = -\sum_{a \in \Gamma_k} \left(\frac{L_a}{L_k} \ln \sum_{l \in C} \delta_{al} \right) \qquad (2\text{-}46)$$

Therefore, it is important to state that the path size correction factor changes between $-\infty$ and 0; however, the original path size factor proposed by Ben-Akiva and Bierlaire (1999) changes between 0 and 1. The modelling with PSCL models is similar to PSL; however, PSC models are based on a random utility structure (Prato, 2009).

The (Cross) Nested Logit

As noted earlier, the MNL model has a limitation for its Independence of Irrelevant Alternatives (IIA) property. The IIA property of the MNL limits the ratio of the choice probabilities for any pair of choices to be independent of attributes of other choices in the choice set. Different models defined different assumptions to rectify the structure of the error distributions of alternative utilities in the MNL models. One of these popular models is the nested logit (NL) model. The NL model is a development of the MNL to treat the limitations of these models with regard to correlations between alternatives (Koppelman & Bhat, 2006).

Additional to the NL model, the cross nested logit (CNL) model is proposed by Prashker and Bekhor (1998) as a mode choice application. The difference between the CNL models and the NL models is that in the CNL models the lower-level alternatives may fit into more than one nest (Prashker & Bekhor, 1998; Ramming, 2002).

These models assumed that routes were chosen within nests which are physically connected to the links in the choice set. As a result, a route may belong to multiple nests. CNL models divided the choice set C_n into m nests C_{mn}. Thus, the choice probability can be written as (Prashker & Bekhor, 1998; Ramming, 2002):

$$P(i \mid C_n) = \sum_{m=1}^{M} P(C_{mn} \mid C_n) P_n(i \mid C_{mn}) \tag{2-47}$$

Where $P(i \mid C_n)$ is the conditional probability of choosing route i in choice set C_n. The choice probabilities of choosing route i in nest m can be defined as:

$$P\left(i \mid C_{mn}\right) = \frac{\alpha_{mi} \exp(V_{in})}{\sum_{j \in C_{mn}} \alpha_{mj} \exp(V_{jn})} \tag{2-48}$$

$$P\left(C_{mn|} \mid C_n\right) = \frac{\exp(V_{C_{mn}} + \mu_m I_{C_{mn}})}{\sum_{l=1}^{M} \exp(V_{C_{ln}} + \mu_m I_{C_{ln}})} \tag{2-49}$$

For the Cross-Nested Logit (CNL) model,

$$I_{C_{mn}} = \ln \sum_{j \in C_{mn}} (\alpha_{mj} \exp(V_{jn}))^{1/\mu_m} \tag{2-50}$$

By combining these terms:

$$P_n\left(i \mid C_n\right)=\frac{\sum_{m=1}^{M}(\alpha_{mi}\exp(V_i))^{\frac{1}{\mu_m}}\left(\sum_{j\in C_{mn}}(\alpha_{mj}\exp(V_i)^{\frac{1}{\mu_m}}\right)}{\sum_{m=1}^{M}\left(\sum_{j\in C_{mn}}\left(\alpha_{mj}\exp(V_i)^{\frac{1}{\mu_m}}\right)^{\mu_m}\right)} \qquad (2\text{-}51)$$

Where α_{mk} are inclusion coefficients (0≤ α_{mk} ≤1) showing the percentage of the link m used by the generic alternative route k. Prashker and Bekhor (1998) defined a coefficient regarding the links in a route:

$$\alpha_{ai}=\frac{L_a}{L_i}\delta_{ai} \qquad (2\text{-}52)$$

where

L_a the length of link (nest) a,

L_i the length of route i, and δ_{ai} is the link-path incidence dummy, which equal to one if route k uses link m and zero otherwise,

μ_m the nesting coefficients (0≤ μ_m ≤1) and it converts the CNL model to the MNL model when the it is equal to one (Prato, 2009).

The CNL model has computational and behavioural limitations. From a computational point of view, for a realistic network size, the nesting structure could become fairly complex. From a behavioural point of view, the nesting coefficient often comes close to one, shifting the CNL model to a MNL model (Prato, 2009; Prato & Bekhor, 2007; Ramming, 2002).

Paired Combinatorial Logit

The paired combinatorial logit (PCL) model is a GEV (generalized extreme value) model proposed by Chu (1989) and developed by Koppelman and Wen (2000) and Prashker and Bekhor (1998). In this approach, the probability of routes that may be chosen between a couple of alternatives within the choice set can be defined as:

$$P_k=\sum_{k\neq j}P(kl)P(k|kl) \qquad (2\text{-}53)$$

where

$P(kl)$ the marginal probability of choosing the pair (k,l) between the $n(n-1)/2$ possible pairs,

$P(k \mid kl)$ the likely possibility of choosing route k given the chosen binary pair (k,l).

The PCL model presented independent similarity relationships for each pair of alternative routes. However, because the large number of pairs of alternatives increases the number of nests and consequently magnifies the computational process, the model is not practical in the real, large networks (Prato, 2009).

Researchers suggested a number of Generalized Extreme Value (GEV) models which rectify the irrelevant alternatives (IIA) property of the multinomial logit model by relaxing the independence assumption between the error terms of choices. This means that a GEV error structure aimed to describe the unknown components of utility is dissimilar to the independent extreme value error formation used in the MNL models. All GEV models can be changed to the MNL model when the correlation value takes values that reduce the correlations between each pair of choices (Koppelman & Bhat, 2006).

Several Non-GEV models (e.g. Multinomial Probit, Logit Kernel with Random Coefficients, Logit Kernel with Factor Analytic Approach) also consider random variation and correlation between unknown factors over time. However, these models presented a costly and complicated computational process for the route choice modelling and did not present a closed-form explanation for the choice probabilities (Prato, 2009).

2.3.4 Route choice approaches and accessibility

The accessibility models typically applied the travel time as the cost of the travel between each pair of O-D. Reviewing these models also revealed that they used several assumptions for calculating adopted travel time that caused inaccuracy in the accessibility models. For example, Liu and Zhu (2004) applied a shortest path algorithm to generate the shortest path by incorporating only the travel time to the transit network, the travel time through the network and the travel time from the transit network to the destination. This approach did not include other attributes for travel time estimations, such as waiting times, transfer times between transit routes, or changing headway times depending on time of day (Lei & Church, 2010).

To solve this shortcoming, O'Sullivan, et al. (2000) developed a shortest path method for a multimodal network based on the Dijkstra algorithm (Dijkstra, 1959) by including the possible transfer times and the average of the waiting times along with the walking times to transit stations, the in-vehicle travel times, and the walking times to the opportunities. The Dijkstra algorithm is generally designed to find the shortest path from a given origin to all possible opportunities. To simplify the process O'Sullivan, et al. (2000) assumed bus travel with a constant speed throughout the network, which is often not the case. The waiting time for making a transfer was assumed to equal half the headway time following the boarded route. The model also neglected the temporal effects associated with the time of day a trip may be made or the day in which a trip is made (Lei & Church, 2010).

Lei and Church (2010) developed an approach, to include an accurate waiting time, by modifying the Dijkstra algorithm. Their proposed method could be used to calculate the time to travel from a point of origin, starting at a specific time, to all possible opportunities. The proposed procedure was to label the network backwards, decreasing the latest arrival time (LAT) until the origin or starting location is reached. This procedure helped to identify the route which would take the smallest amount of elapsed time to reach the desired opportunity by the fixed arrival time (Lei & Church, 2010).

As explained in the listed route choice algorithms, there is a mutual trend between researchers to improve the shortest path calculation by increasing the accuracy of travel time calculation. However, the role of the route choice model in these accessibility models is to pick up a single shortest path. These approaches to the accessibility could not capture travellers' diversities and preferences in a real network.

An exception to the above statement, PTALs (Public Transport Accessibility Levels), applied a basic approach to incorporate the effect of route choice into the accessibility model. The model proposed to sum up the estimated travel time for all available routes and to consider a weighting factor in favour of the shortest route (Kerrigan & Bull, 1992). The PTALs model aimed to capture the route choice effects but, as explained in the review of transit accessibility models, it could not propose a robust approach for incorporating travellers' choice into the model.

It is important to note that route choice in a transit system may be affected by a number of factors other than travel time. Minimizing the fare, the number of interchanges, walking distances, or waiting times are all possible travellers' preferences for a route choice. In other words, the routes with the maximum utility are subjected to the socioeconomic characteristics of travellers and to the attributes of the transport system such as travel time, fare and comfort (O'Sullivan, et al., 2000).

Reviewing transit accessibility approaches revealed that some researchers (Bhat, et al., 1999; Bhat, et al., 1998; Davidson, 2008) acknowledged the importance of travellers' choice in the accessibility estimations. However, possibly due to inherent complexities of transit services, the passenger choice applied mainly to the choice of mode or destination, and the impedance part of travel estimated deterministically using the path with the highest utility.

As a result, incorporating travellers' route choice preferences into the accessibility estimation is one of the motivations in this research.

The following section outlines the difficulties of transit path choice modelling in the transit network.

2.3.5 Transit route choice approaches

Transit path choice modelling in a real transit network can be a difficult process as it needs to incorporate different aspects of the transit network, such as transfer difficulties, multimodality of transit services, and different frequency of public transit routes. In a real transport network, the number of choices available to the travellers is very large, if not indefinite (Van der Gun, 2013).

Additionally, current transit route choice approaches are criticised because of their limitations to observe and capture the strategic choice behaviours.

Behind these difficulties is the fact that the observed transit routes cannot always describe the choices actually made. For example, the observed trip choice of taking a particular bus route i at stop A to travel between an origin-destination (O-D) pair may not show the entire choice. This choice may not be exclusively related to the attributes of route i; it would be a result of other attributes associated with stop A or the availability of other transit routes departing from stop A.

Therefore, the direct observations of simple path choices may systematically fail to capture all the situations that the travellers may experience when they travel through the transit system, as all attributes for these complex choices may not be exclusively observed.

Research over the past fifty years, especially in transit path assignment has presented different transit route choice models, varying from simple path choice techniques to adjustable and complicated strategy path choice methods. Examples of situations that passengers may consider more complicated choices than single elementary OD paths include transit networks with common routes serving the same corridors (Chriqui & Robillard, 1975; Marguier & Ceder, 1984), the importance of strategies and hyperpaths in high frequency networks and overlapping lines (Nguyen & Pallottino, 1988; Spiess & Florian, 1989), and the availability of real-time information on the status of transit vehicles (Cats, Koutsopoulos, Burghout, & Toledo, 2011; Gentile, Nguyen, & Pallottino, 2005; Hickman, 1996; Hickman & Wilson, 1995).

The review of existing transit assignment and route choice approaches showed that they acknowledged and reported for the complexities of travellers' strategic behaviour (Cats, et al., 2011; Desaulniers & Hickman, 2003; Fu, Liu, & Hess, 2012). To treat these complexities in the transit assignment methods, the literature usually proposed simple objective functions, reflected in the limited attributes that a user may consider (mainly total travel time); however, these approaches typically failed to capture travellers' choice behaviour in the network.

Several researchers proposed to consider different strategies for capturing travellers' choice behaviour. Schmöcker, Shimamoto, and Kurauchi (2013) classified the existing methods into two categories. The first group of transit assignment studies takes strategies into account but mostly ignores the dissimilarities among different utility attributes, such as transfers or walking distances. The second group of models includes behavioural models which can consider these dissimilarities; however, these types of transit assignment literature deal mostly with elementary path choices, ignoring hyperpaths and the variability of boarding routes (Liu, Bunker, & Ferreira, 2010). A hyperpath can be defined as a group of possible paths which are identified by the travellers for each stop (Fonzone, Schmoecker, Kurauchi, & Hassan, 2013).

On the other hand, an analysis carried out on the smart card data from London (Oyster card) revealed that most travellers do not travel through fixed routes for their regular commutes (Kurauchi, Schmöcker, Shimamoto, & Hassan, 2014). This statement supports the importance of hyperpaths and strategies in transit path choice analysis.

(Fonzone, Schmocker, Kurauchi, & Hassan, 2013; Fonzone et al., 2010) also confirmed a similar finding from a web-based survey that was distributed among international respondents from 106 cities in 25 countries. The results of this survey also revealed that traveller preferences may be different from country to country; for example, Chinese PT users do not use complex strategies in their commutes.

To overcome this limitation in strategy choice modelling, Kurauchi et al. (2012) proposed a hyperpath choice model, by including in-vehicle time, waiting time and number of transfers for the utility attributes of the choice model. They applied a web-based stated preference survey with hypothetical scenarios in an abstract network (three routes and up to seven hyperpaths). Hyperpath choice model or strategic choice model is a technique to generate a choice set for the routes which identified by travellers to boarding stop or destination. Their proposed model used a cross-nested logit structure, with bus routes defined as the nests, and with all the possible hyperpaths including a nested route as its members. This cross-nesting model structure was successful in rectifying the correlations among the alternative hyperpaths, and significant model fit improvement was reported. Their analysis revealed dissimilarities in the generated hyperpaths by different socio-demographic groups and for different travel purposes (Kurauchi, et al., 2012). A benefit of such a preference survey is that the information about passenger strategy can be collected which is difficult, if not impossible, to gather from revealed preferences in a typical travel survey. However, there is no guarantee that the results of the stated preference survey are realistic when the estimated model is applied to a real-sized and dense transit networks.

Hereof, Fonzone and Bell (2010) argued over human rationality and limitations on computational ability in making complex hyperpath alternatives in real-size dense networks. By assuming these realistic limitations, they suggested a myopic hyperpath estimation method and defined a limit on the size of the hyperpath that is handled by the travellers.

In another study in a local city in Japan, Schmöcker, et al. (2013) identified the inconsistency between the observations (bus route boarding records) and the hyperpath choices. To overcome this issue, they proposed a bi-level discrete choice model. They suggested a hierarchical model that assumed the choice of hyperpath at the higher level is based on personal preferences; at the lower level, deterministic probabilities of boarding the hyperpath routes are related to their frequencies (Fonzone, Schmocker, et al., 2013). The proposed model utilised attributes of waiting time and in-vehicle time to calculate hyperpath utility coefficients. However, due to missing access information in fare card datasets, the choice model described the path choices from given departure stops, ignoring travellers' preferences and choices in the access stops.

In summary, reviewing the transit route assignment techniques and the transit route choice models revealed that although a number of researchers (Fonzone & Bell, 2010; Fonzone, Schmocker, et al., 2013; Kurauchi, et al., 2012) developed transit assignment models to consider transit users' choice behaviour, these approaches have two major drawbacks. First limitation is related to computational complexity in making hyperpath alternatives in the real-sized transit networks. Second, these approaches ignored the important element of access legs from the origin to the transit network and captured only the travellers' path choices from given departure stops.

2.4 CONCLUSION

Measuring accessibility aims to quantify the total net benefit that residents of a particular geographic area can receive from the proximity or ease of travel to amenities (or needs) located elsewhere. Reviewing existing accessibility approaches, particularly transit accessibility models, has revealed that the drawback to these models is not limited to capturing the actual benefits that a traveller can gain from ease of access (benefit side). These models have another challenge: properly capturing the difficulties that travellers may experience in their journey to actual opportunities (cost side). This research thus focuses on the cost side (network side) of accessibility, aiming to explain actual travellers' difficulties in accessing to actual destinations through transit system.

The literature reviews has revealed three main challenges in the existing network accessibility models.

The first drawback to the existing concepts for estimating the transit network accessibility is to ignore the travellers' behaviour and the fine details of spatio-temporal attributes of transit systems. These approaches either typically proposed simple objective functions, mainly the average or fastest travel time, to explain the transit impedance or estimated only the accessibility impedance to transit corridor (transit stops). These simplifications cannot capture the effects of travellers' behaviour and spatio-temporal transit characteristics on transit accessibility.

Secondly, the existing transit accessibility models could not capture the benefits that travellers can gain from diversity of transit network. Although, researchers acknowledged the importance of transit diversity in the accessibility estimation, literature review revealed two limitations in the transit assignment models: first, the existing transit assignment approaches captured only the travellers' alternatives from given departure stops and ignored access legs from the origin to the transit network. Another shortcoming in the existing transit route assignment techniques is related to complexity of generating hyperpaths for all strategies in the real-sized transit networks.

Thirdly, although capturing the stochasticity of travellers is not a new concept in the transport and accessibility models, these approaches have either used a random-utility approach for the choice of destinations (e.g. parallel conductance and LUPTAI models) or have sought to capture the stochasticity of the transit services only (Hickman, 2001; Hickman & Bernstein, 1997). As a result, the existing approaches did not aim to capture the stochastic error term that is known to exist in the perceptions of transit network among the travellers.

As a result, this research aims to improve the network accessibility estimation by focusing on the following directions:

- Capturing travellers' behaviour and the fine details of the spatio-temporal attributes of the transit system
- Considering travellers' preferences and network diversities in the transit system
- Capturing stochasticity or subjectivity in perceptions of transit network among the transit users.

The proposed modelling framework for the developed model and modelling calibration will be described in the following chapter.

Summary of the chapter's contributions

Outcomes

- Exploring the weaknesses and limitations with existing accessibility models and particularly transit accessibility models
- Explaining the importance of incorporating the multiple high-utility paths instead of the traditional simple route approach in the transit accessibility estimation
- Clarifying the advantages and limitations of route set generation techniques and route choice approaches
- Discussing the major shortcomings with current path choice approaches in the transit system.

Key findings

- Existing transit accessibility approaches could not capture the actual transit users' difficulties in their journeys from origin to destination (including "first-and-last mile" problem)
- Existing models ignored the transit users' preferences and their subjectivities in the transit network.

Limitations

The literature review identified two major limitations with the existing transit path choice approaches:

- Capturing travellers' path choice behaviour from given departure stops and paid no attention to travellers' preferences about access stop choices.
- Limiting the size of the path choices that is handled by the travellers to manage the complexities of travellers' strategic choices.

Chapter 3: Modelling Framework and Choice Model Calibration

3.1 INTRODUCTION

The review of existing transit accessibility models has revealed several drawbacks with the existing approaches for measuring the accessibility of transit network. First, the impedance element in these approaches, mainly represented by simple distance or travel time to destinations, would not lead to capture travellers' behaviour and the fine details of the transit service characteristics. Second, the existing transit accessibility models could not capture the benefits that transit users can gain from the transit network diversity. Third, these approaches could not capture stochasticity in perceptions of transit network among the transit users.

Although some researches in the context of the utility-based approach have attempted to estimate transit accessibility by considering travellers' behaviour, these approaches again either 1) do not capture transit users' preferences in the transit network (impedance side), or 2) do not estimate the transit network accessibility for the entire of the transit journey (including "first-and-last mile" problem), or 3) do not capture the indeterminacies of passengers in perceptions of transit network.

Bhat, et al. (1999) proposed a mode choice accessibility model by estimating the network utility based on in-vehicle-time and out-of-vehicle-time as well as the composite cost of all three modes (auto, transit and walk) as impedance attributes. However, their model does not capture the travellers' preference and stochasticity in their perception of the transit network, as it estimates the impedance of the network based on the highest systematic utility of a single path.

Another approach to estimate the transit network accessibility, proposed by Rastogi and Rao (2003), considered the travellers' socioeconomic characteristics, the environmental effects and the transport attributes as model attributes. However, this model captures only the random utility of travel from origin to transit stops[1] and it does not aim to capture the impedance of transit system.

LUPTAI (Davidson, 2008), another model which measures the transit accessibility in the context of random utility approach, incorporates travellers' preferences into the model, but the random utility model is applied only to choice of

---

[1] The term "stop" or "transit stop", in the context of this dissertation, is reserved for "bus stops", "railway stations", and "ferry terminals".

destinations, while the impedance part of the model is estimated again systematically using the shortest path and the generalised cost of trip. Accordingly, the model cannot take account the travellers' preferences in the transit network.

To address these identified gaps in the literature, this research develops an access stop choice model to capture travellers' behaviour as well as their subjectivity in perceiving the transit network.

Modelling the choice model at the stop level not only allows us to capture transit users' stop choice behaviour (e.g. capture travellers' perception about the amenities of the stops) but also can solve the known problems with strategic travellers' choices and makes the combinational of alternatives possible.

As a result, the developed choice model needs to answer these key questions:

- Which attributes are important for travellers when they choose their path/stop to a destination through the transit system?
- Do transit users choose their path only because of the desired route attributes? Or are traveller's choices influenced by stop attributes as well?
- Do transit users always choose their path based on highest systematic utility or highest estimated probability?
- How can the proposed model capture the subjectivity and stochasticity in perception of transit network among the passengers?
- How can the developed access stop choice model rectify the correlation among stop/mode alternatives?

This chapter explains the modelling structure and the choice model specification. The calibration results of choice model and the result of model validation will also be discussed in this chapter.

Chapter Outline

Section (3.2) provides an overview of the modelling structure, including the research framework and the proposed model structure. In section (3.3), the modelling datasets utilised in this research are presented: HTS (Household Travel Survey) Data, GTFS (General Transit Feed Specification) Data, GIS Data of network and Public transit facilities data. Section (3.4) describes the specification of the proposed transit access choice model while section (3.5) explains the proposed set generation algorithm and its generated choice sets. Path reasonability checks for the generated choice sets also are explained in this section.

Section (3.6) presents the choice model calibration method and the results of the model calibration. Travellers' subjectivities and their stochasticity in perception of transit network are discussed in section (3.7). In section (3.8), the results of the proposed choice model are validated and, the last section (3.9) summarizes the outcomes of the chapter.

3.2 OVERVIEW OF MODELLING STRUCTURE

In order to understand and model passengers' behaviour when using public transit, this chapter focuses on developing a discrete choice model for the choice of transit access stop. The proposed model needs to incorporate different components of the transit services between given O-D pairs at given times.

Train stations, ferry terminal, and bus stops are defined as travellers' choices (alternatives) for accessing to the public transit network in the proposed choice model. Developing the choice model at the stop level has several theoretical and practical advantages.

As previously noted, due to difficulties with transit strategic behaviour approaches, modelling public transit choice behaviour model has several complexities that are not obvious in other traffic route choice modelling. The transit strategic behaviour can be interpreted as different strategies such as shortest path, safest route or cheapest travel option that different passengers may consider when they choose their path to destination. The Spatio-temporal limitations of service, the importance of transfers, the multimodality of service, and the complex correlations among the paths are some of the main reasons (Cats, 2011) that make the transit choice behaviour model more complex.

Additional to these complexities, the existing approaches have a limitation to observe the strategic choice behaviour of travellers, as the observed data is inconsistent with the actual choices made by travellers. On the other word, the route which has been chosen by traveller (observed transit route) necessarily do not show his/her actual choice when he/she decided to start the trip from origin.

Developing the access stop choice model instead of a path choice model can solve the problem with accurate prediction of path choices due to passengers' strategic boarding/alighting behaviour in high frequency transit networks (Nguyen & Pallottino, 1988; Spiess & Florian, 1989). This approach can also provide an opportunity to capture travellers stop choice behaviour, as the alternative access stops are mutually exclusive and there is a one-to-one incidence among the observations and the choices.

Developing the stop level choice model also allows us to define the proposed accessibility logsum as combination of all possible choices by considering all possible travel strategies which is not possible by hyperpaths strategies due to the combinatorial characteristics of the hyperpaths (Nguyen, Pallottino, & Gendreau, 1998).

As a result, applying the choice model at the stop level not only will help us understand the importance of transit network attributes among the travellers but also, can highlight the subjectivity in the perceptions of the transit system among the passengers.

In this choice model, the observed data or chosen stops were taken from the household travel survey (HTS) for 2009 in SEQ. This data contains travel information for all available public transit modes: train, bus and ferry. It is important to note that the proposed accessibility measurement requires high resolution O-D data which it was not easy to obtain from transport authorities due to privacy reasons.

To generate unchosen alternatives, this research proposed a choice set generation algorithm. This algorithm needs to generate the sets of reasonable access stop choices for all pair of O-D observed journeys; and to calculate the time-dependent service attributes from chosen stops to the destination.

As shown in Figure 3-1, after the sets of access stop choices are generated, the choice model attributes need to be calibrated by applying the generated choice sets (unchosen alternatives) and the observed choices (chosen alternatives). Applying these two data sets in the context of random utility modelling will help us to capture transit users' behaviour and also stochasticity among travellers in their perception of the transit system. Also, to adjust the amount of interdependencies among the stops due to common routes to the destination, three different correction factors at the stop level are designed and calculated. Adding these correction factors before model calibration will let the model to estimate the proper coefficient for these correction terms.

The discrete choice estimation software package, BIOGEME (Bierlaire, 2006), is used to calibrate the model. This package mainly uses the maximum likelihood estimation technique to estimate coefficients associated to each attribute of the choice. By having the model coefficients, we will be able to calculate the utility values based on the observed travellers' behaviour between each pair of O-D in the transit system.

In order to validate the modelling output, the HTS dataset is also split using SPSS (Leech, Barrett, & Morgan, 2012), a standard statistical software package, to select randomly 80% of the records for the calibration dataset, and the remaining 20% for validating the model.

In the review of transit accessibility literature, we also acknowledged that there is another drawback with existing transit accessibility models: they cannot capture the travellers' preferences and their subjectivity in the transit route choice. To overcome these limitations with the existing approaches, we need again to generate sets of choices between all the given OD pairs. This set generation will allow us to capture the effect of all available transit paths between given origins and destinations on the transit accessibility (see modelling estimation in Chapter 4).

As it is indicated in the below flowchart, after generating the stop choice set to capture the travellers' preferences and subjectivities, the accessibility values for the choice set needs to be calculated and visualised. Followed by, these values will be validated systematically by the observed land value data. This process will also be explained in Chapter 4. In the final step of this research, different policy sensitivity analyses will be carried out, to highlight the sensitivity of model to capture policy changes in the transit system (see Chapter 5). These policy sensitivity analyses will also be helpful to quantify passengers' behaviour and their perception about changes in the transit system, particularly when existing known stochasticity among the travellers makes the model difficult to identify optimum policies.

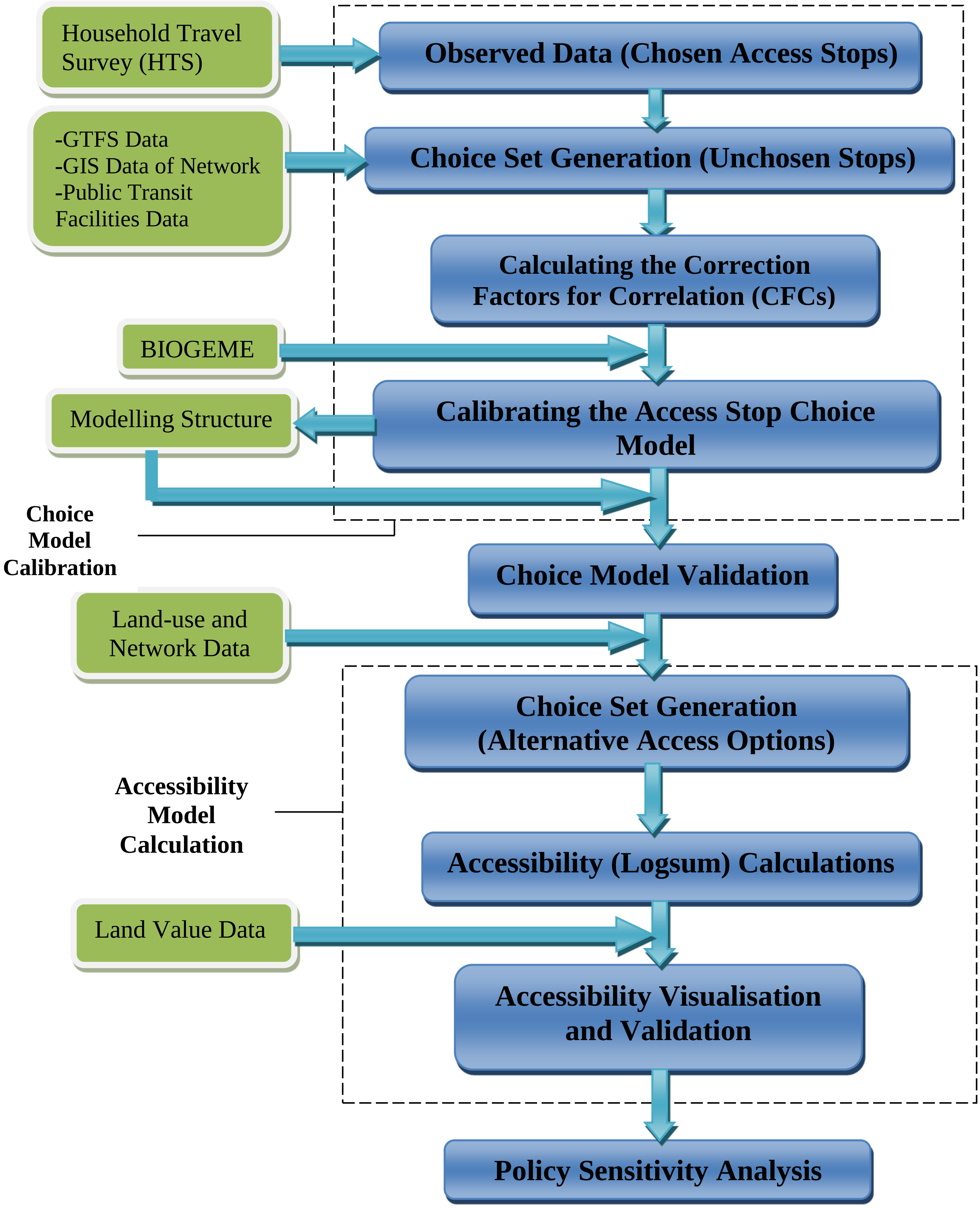


Figure 3-1: Proposed framework for estimating public transit accessibility

The following section provides a brief description of the case study datasets used in this research.

3.3 MODELLING DATASETS

The prototype for the proposed accessibility measurement technique was developed and tested in the context of Southeast Queensland (SEQ), Australia, which includes the Brisbane Statistical Division (BSD), the Gold Coast City Council and Sunshine Coast Regional Council areas.

For this purpose, the following data sets of SEQ are applied to the proposed high resolution framework for measuring the transit network accessibility. Firstly, to investigate the travellers' behaviour, this study applied household travel survey (HTS-2009) data as an observed data set. This dataset contains travel data for all available public transit modes: train, bus and ferry. Secondly, to compute the travel time details (e.g. in-vehicle travel time, waiting time), this research utilised general transit feed specification (GTFS) of SEQ for 2009. This data provides the time-dependent transit schedule data of SEQ in 2009. Thirdly, to compute the exact walking distances in the real walking network, the proposed model utilised a high resolution GIS network of SEQ. Finally, to incorporate the transit stops' attributes into the model, the research employs transit stop amenities data for all the transit stops of SEQ. These modelling datasets are described in the following section.

3.3.1 HTS (Household Travel Survey) data

One of the important datasets for all transport infrastructure plans is the travel data of households. All transport planning authorities and operational agencies require these reliable trip data to be able to make educated policy and planning decisions. Household travel survey (HTS) is a primary source of information for understanding and quantifying travellers' usage behaviour and preferences when using the actual transport network. This study used the data of SEQ travel survey in 2009 includes (DTMR, 2010b, 2010c, 2010d):

- All occupied private residential households within the study area defined by the Brisbane Statistical Division, the Gold Coast LGA (Local Government Areas) and Sunshine Coast within the LGAs of Noosa, Maroochy and Caloundra (see Figures 3-2).
- All individuals (including visitors) staying at these households on the night prior to the household's travel day;

- Travel made by persons aged 5 and above on all days of the week during the survey period.

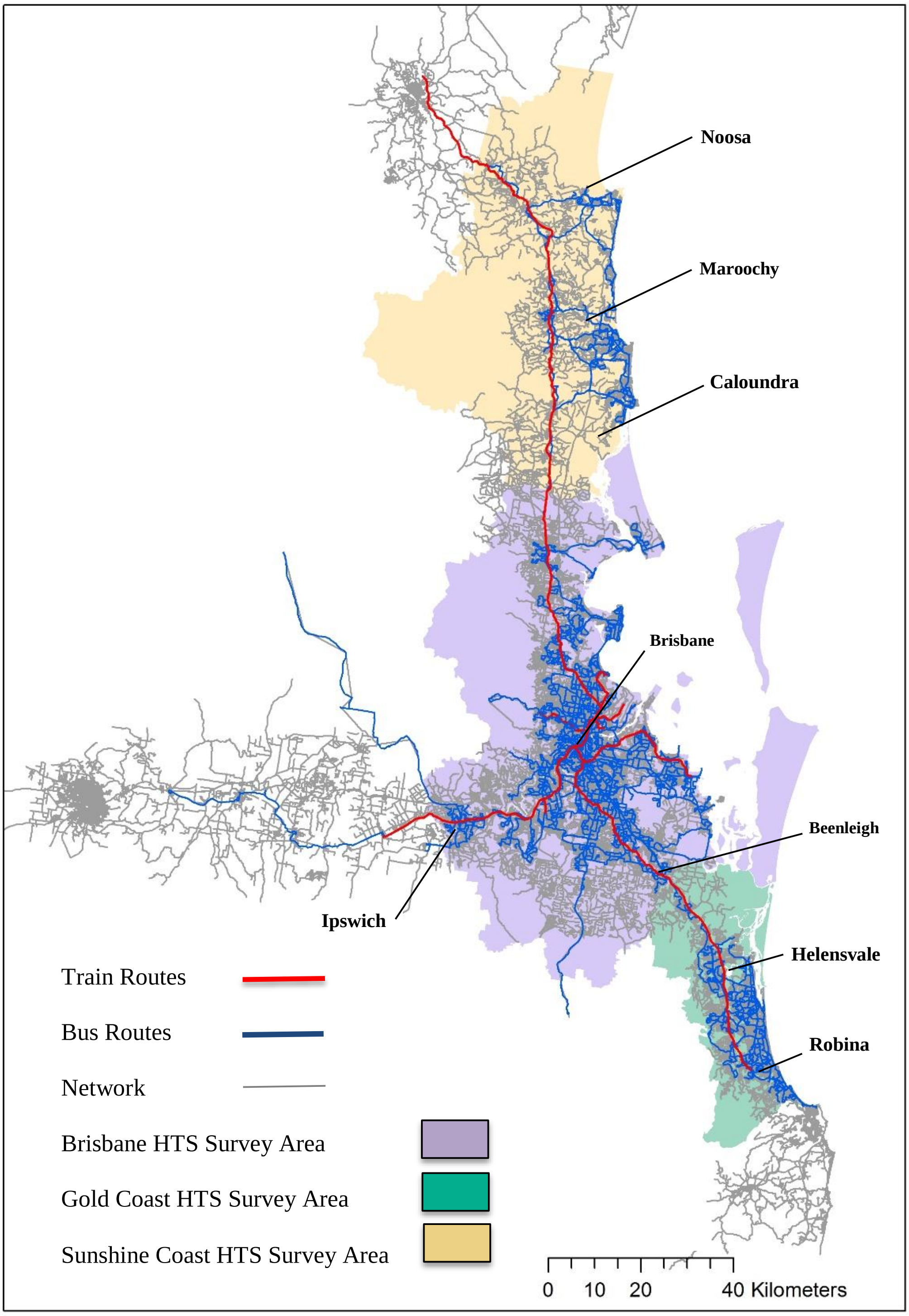


Figure 3-2: The HTS-2009 Study Areas (DTMR, 2010b, 2010c, 2010d)

According to HTS report for Brisbane, the overall sample size of responding households for the Brisbane study area is 3550, with a 6.5% sampling rate (based on random sampling). For the Gold Coast, the sample size is 2940, with a 4.4% sampling rate; for the Sunshine Coast, the sample size and sampling rate are 2940 and 5.2% respectively.

HTS-2009 includes a wide range of information regarding household characteristics (e.g. number of members in household, dwelling type, number of household vehicles), the socio-economic characteristics of households (e.g. age, gender, income, employment status), household vehicle data (e.g. manufacturer, age, associated costs) and trip information of travellers (e.g. trip data for origin, trip data for destination, travel purpose information, trip mode) (DTMR, 2010b, 2010c, 2010d).

In this research, all travel records using public transport, with walking section of access, egress and transfer(s), are extracted from the HTS data. The total number of journeys with this order are 1692, including 1434 transit trips without a transfer, 229 journeys with a single transfer, 26 journeys with two transfers, and 3 journeys with three transfers. Regarding the mode of the access stop, 1176 travellers had chosen bus stops, 492 travellers had chosen train stations, and 24 had chosen ferry terminals. Table 3-1 shows the combination of modes and number of transfers in the extracted HTS data for the choice modelling.

Table 3-1: Mode combination and number of transfers in the HTS sample

Number of Samples	Number of Transfers	Leg of Travel						
		Mode 1	Mode 2	Mode 3	Mode 4	Mode 5	Mode 6	Mode 7
1427	0	Walk	Transit	Walk				
168	1	Walk	Transit	Transit	Walk			
57	1	Walk	Transit	Walk	Transit	Walk		
19	2	Walk	Transit	Transit	Transit	Walk		
7	0	Walk	Transit					
3	2	Walk	Transit	Walk	Transit	Transit	Walk	
2	2	Walk	Transit	Walk	Transit	Walk	Transit	Walk
2	3	Walk	Transit	Transit	Transit	Transit	Walk	
2	1	Transit	Transit	Walk				
2	1	Walk	Transit	Transit				
2	2	Walk	Transit	Transit	Walk	Transit	Walk	
1	3	Walk	Transit	Transit	Transit	Walk	Transit	Walk

3.3.2 General transit feed specification (GTFS) data

A general format for public transportation schedule data was initially introduced by Bibiana McHugh (TriMet transit agency) in 2005. This data format was then developed by Google and Portland TriMet (Roth, 2010). In 2006, Google introduced Google Transit, an additional service to Google Maps that enables users to plan public transport journeys from origin to destination (Hadas, 2013).

To implement the service simply and to promote agencies to join, Google established a unified specification called General Transit Feed Specification (GTFS). The GTFS data provides a template structure for public transit agencies to publish their transit schedule data and their real-time service characteristics, according to (GoogleDevelopers, 2012). This also provides an opportunity for transport researchers to analyse public transport performance.

The GTFS data includes six required data files and seven optional files about characteristics of the transit network.

Table 3-2 describes the content of these files. Generally, GTFS data provides information about the types of stops and their locations, route specifications, trips and associated routes, and public transit time tables. It can also provide other optional information such as fare and transfer specifications.

This research utilised the GTFS data of SEQ for 2009 to generate the choice sets for the proposed access stop choice model. Because historical data of GTFS data for SEQ in 2009 was not available, the GTFS data for SEQ retrieved and converted from transit network data and Translink service schedule data in May 2009. The SEQ transit network included 14,442 stops, 767 routes, and 33,897 timetabled vehicle trips, with different services on weekdays and weekends for all three transit modes (train, bus, and ferry). Figure 3-3 shows a snapshot of the density of the transit network and spatial distribution of transit stops at the CBD, visualised from generated GTFS data.

Table 3-2: The General Transit Feed Specification (GTFS) data tables (GoogleDevelopers, 2012)

Data Table	Description	Attributes	Comments
Agency	Describes transit agency information that provides the data.	agency_id, agency_name, agency_url, agency_timezone, agency_phone, agency_lang	Required
Stops	Includes locations of all transit stops (pick up and drop off locations).	stop_id,stop_name,stop_desc, stop_lat,stop_lon,stop_url, location_type, parent_station	Required
Routes	Contains transit routes information. A route represents a group of trips that are displayed to riders as a single service.	route_id,route_short_name, route_long_name,route_desc, route_type	Required
Trips	Represents trips and their associated routes. A trip is a sequence of multiple stops that occurs at a specific time.	route_id,service_id,trip_id, trip_headsign,block_id	Required
Stop Times	Includes time tables of public transit arrives and departs for each stop.	trip_id,arrival_time,departure_time,stop_id,stop_sequence,pickup_type,drop_off_type	Required
Calendar	Shows dates of services for all service IDs using a weekly schedule to specify when service starts and ends.	service_id,monday,tuesday,wednesday,thursday,friday,saturday,sunday,start_date,end_date	Required
Calendar Dates	Describes exceptions for the service IDs defined in the calendar file. This file may be used in place of a calendar file if calendar dates contains all dates of service.	service_id,date,exception_type	Optional
Fare Attributes	Includes fare information for all transit agency's routes.	fare_id,price,currency_type,payment_method,transfers,transfer_duration	Optional
Fare Rules	Describes rules for applying fare information for transit agency's routes.	fare_id,route_id,origin_id,destination_id,contains_id	Optional
Shapes	Explains rules for drawing lines on a map to represent transit agency's routes.	shape_id,shape_pt_lat,shape_pt_lon,shape_pt_sequence,shape_dist_traveled	Optional
Frequencies	Defines headway between trips for routes with variable frequency of services.	trip_id,start_time,end_time,headway_secs	Optional
Transfers	Describes rules for making connections at transfer points between routes.	from_stop_id,to_stop_id,transfer_type,min_transfer_time	Optional
Feed Info	Includes extra information about the feed which including publisher, version, and date of expiry.	feed_publisher_name,feed_publisher_url,feed_lang,feed_start_date feed_end_date, feed_version	Optional

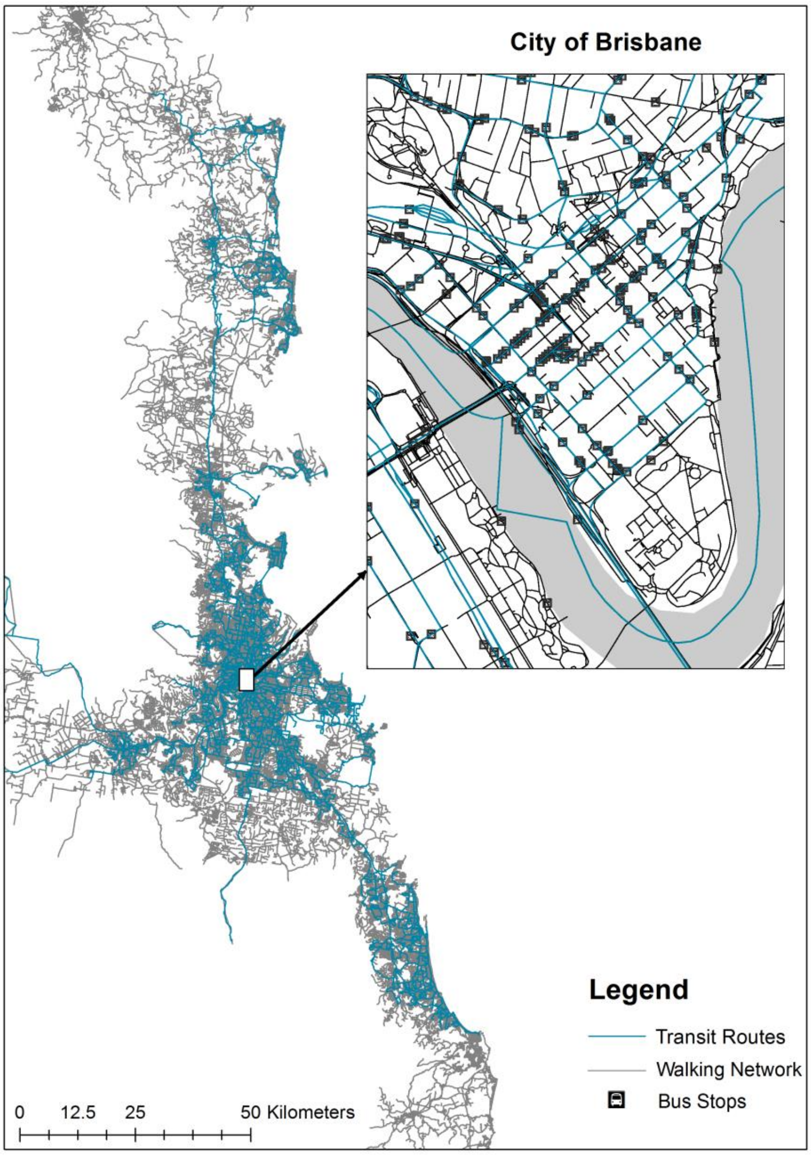


Figure 3-3: Density of bus stops in Brisbane CBD

3.3.3 GIS data of network

The proposed model needs to apply the GIS walking network to compute the actual walking distances for all HTS observed trips and also all non-observed (generated) trips in the real walk network. The walk network data for SEQ was downloaded from "OpenStreetMap", which includes local streets, sidewalks, crosswalk connections, walking ramps, footways, and stairways in greater Brisbane, the Gold Coast and the Sunshine Coast area. The walk network included 250,000 nodes and 340,000 links. ArcGIS (Sandhu & Chandrasekhar, 2006) is applied in this research to compute walking paths and to match the geographic location of the stops in the network. The walking leg computation includes calculating the walking distances from origin to transit stops (access), walking from a stop to another stop (transfer) and walking from transit stops to destinations (egress) for all pair of O-D journeys including observed HTS trips and the generated route choices. Figure 3-4 shows a snap shot of the transit network, extracted from GTFS data, and the O-D locations for observed data, extracted from the HTS dataset.

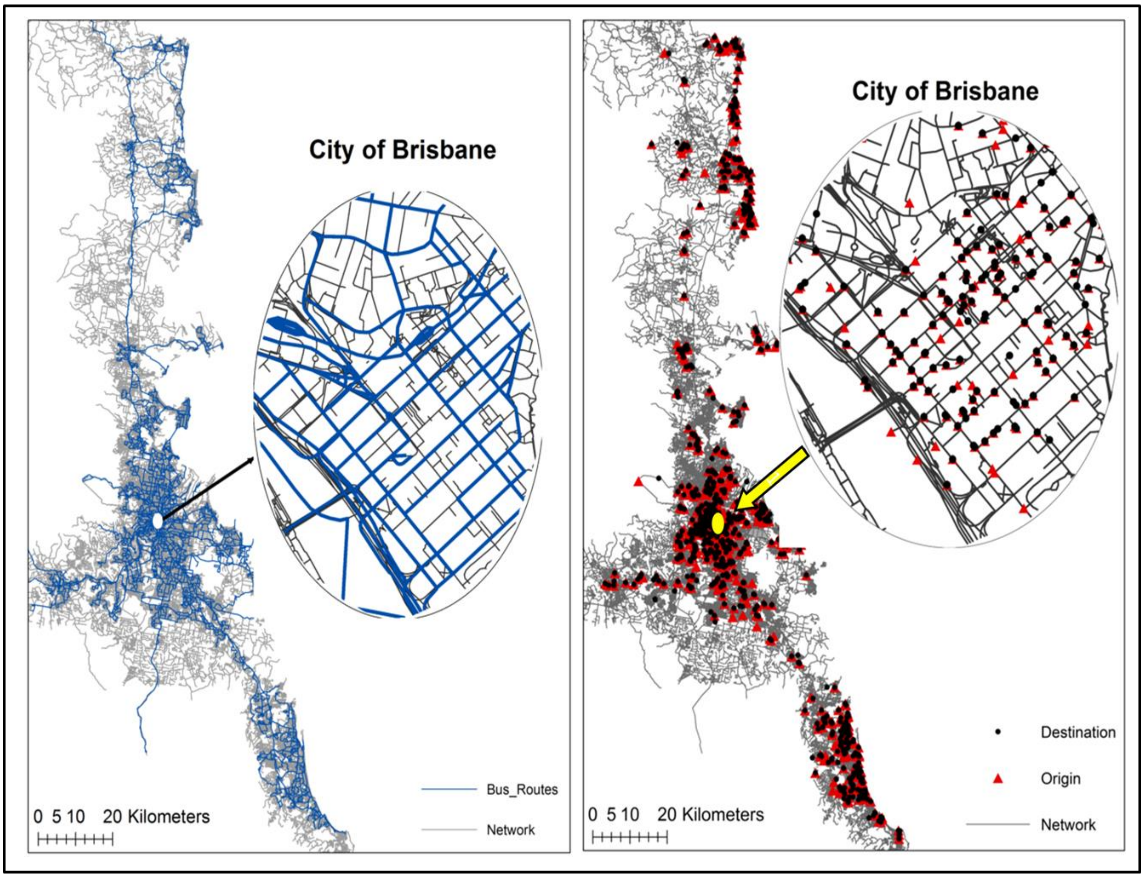


Figure 3-4: SEQ Transit Network and HTS Observed Origins and Destinations Locations

3.3.4 Public transit facilities data

Transit facilities data for all the transit stops were provided by the Queensland Department of Transport and Main Roads (DTMR). This dataset includes the information about the stop amenities, such as shelter, illuminations, access walkways, boarding slabs, information maps that will be coded in the model. As provided facilities data by DTMR do not use identical stop coding system with other obtained data such as GTFS and HTS data, we performed a geo-coding process to match the geographical location of transit stops in all collected datasets which we used in the modelling process. These attributes are shown in Table 3-3.

Table 3-3: Public transit facility attributes

Attribute Variable	Description
Shelter	Variable indicating a sheltered stop
Stop Light	Variable indicating an illuminated stop
Street Light	Variable indicating an illuminated street
Boarding Slab	Variable indicating existence of a boarding slab
Foot Path	Variable indicating existence of foot path
Map	Variable indicating existence of printed map/schedule at the stop

3.4 TRANSIT ACCESS STOP CHOICE MODEL SPECIFICATIONS

There is an essential explanation about the specification of the access stop choice model and its application in this research. Although the transit passenger choices are modelled at the access stop level (instead of at full path choices), the full path attributes of all reasonable paths originating from each access stop to the actual destination are summarised in the attributes of that alternative.

There are two important reasons for modelling the access stop choices instead of the path choices. First, passengers' strategic boarding/alighting behaviour in high frequency transit networks necessitates the consideration of the "attractive set" of boarding routes (Spiess & Florian, 1989) and travel "hyperpaths" (Nguyen & Pallottino, 1988) for accurate prediction of path choices. Some recent research has targeted the utility-based estimation of passengers' attractive sets and hyperpaths. However, such estimation has special data requirements, such as hyperpath choice questionnaires (Kurauchi, et al., 2012) that are not easily designed and fielded by researchers. (Schmöcker, et al., 2013) developed a bi-level discrete choice model to estimate hyperpath choices using a fare card data set. However, in typical transit fare card data sets the important element of access legs from the origin to the transit network is missing. Second, the proposed accessibility calculation in this research is based on the logsum composition of all possible alternatives; however, this requires explicit enumeration of all possible travel strategies (hyperpaths), which is known to be impractical due to the combinatorial nature of the hyperpaths (Nguyen, et al., 1998).

The access stop choice model in this research is also structured as a nested logit model which assigned all the stops associated with each mode, as members of that mode's nest. This nested structure can incorporate the correlation among the stops at the mode level. Three nests (bus, ferry and train) for the three available modes were originally defined in this model. However, after preliminary analysis of the data, to maintain the significance of all nest coefficients at the 0.05 level, the nests were reduced to two nests, train and no_train. Merging the bus and ferry nests seems to be controversial as bus and ferry provide their services on the different transit networks. However, reviewing the bus and ferry performance in the transit system shows a key similarity. Ferry and bus services have a similar speed in the transit network in compare to train services which serves travellers with higher speed in the network. According to a survey in SEQ, the average speed of train services is 23 km/h while these figures for the bus and ferry services are14 km/h and 15 km/h respectively (DTMR, 2012). This resemblance in characteristics of services which provide by ferry and bus in the transit network makes the proposed nest structure align with our statistical outputs which shows a correlation between the bus and ferry nests. Figure 3-5 shows the preliminary and final nested structure in the model.

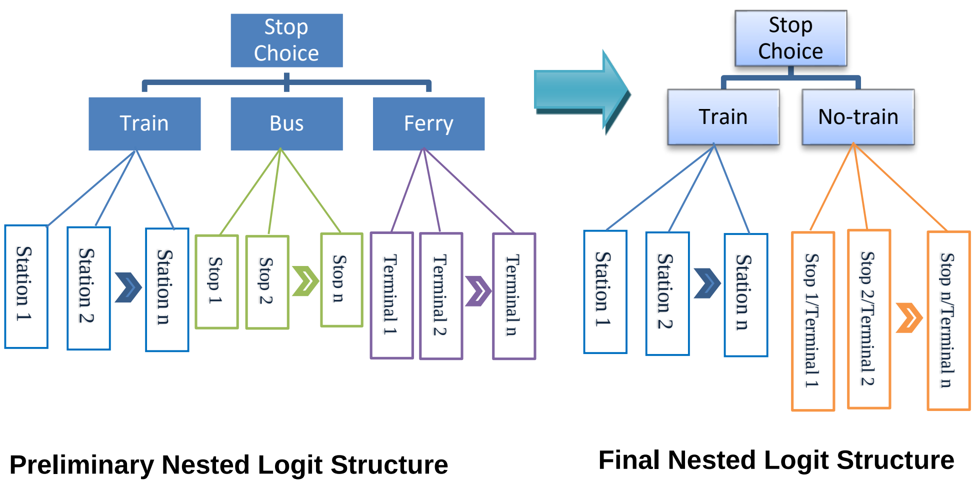


Figure 3-5: Preliminary and final nested structure

The explanatory attributes that are incorporated into the proposed choice model are classified in three groups: 1) facility (amenities) attributes, 2) impedance attributes, and 3) correlation attributes. These explanatory attributes of the model are described in table 3-4.

Facility (amenities) attributes are explained as variables which either describe the stop characteristics, such as availability of shelter, illumination, availability of footpath or boarding slab at the stop, availability of printed transit maps and schedules, or relate to the stop features in some ways such as the mode serving the stop and access walking time from the origin to the stop.

The second category covers the impedance attributes, which are described and calculated in direct and aggregate formats. As shown in the proposed model algorithm (Figure 3-1) and described in section 3-4, in the path generation process a set of reasonable paths are enumerated, departing from the chosen stop to the destination, at the given departure time. The impedance attributes need to be extracted in the process of the path enumeration. The direct attributes contain the features of the best paths from different perspectives. For instance, the travel time of the path that has the fastest travel time among all paths from the stop to destination is one of the direct attributes in this research. Number of transfers of the path that requires the least number of transfers is another direct attribute for the proposed choice model.

The aggregate impedance attributes such as the average travel time and number of transfers among all reasonable paths, the number of possible routes from the stop to destination, and the total frequency of all routes serving the destination account for the aggregated characteristics of the group of paths. The explanations of all these attributes are provided in Table 3-4.

Three proposed alternatives for correction factors to rectify the correlation among the access stop choices are the third group of attributes in the proposed model. These correlations among the stops are the result of route commonalities among the stops. As explained in the literature review, the fundamental assumption in the multinomial logit (MNL) models is that the random components of the utility of the choices are identically distributed (IID) and independent (Ben-Akiva & Lerman, 1985).

Table 3-4: Explanatory Attributes of Model

Type	Attribute Variable	Description
Facility	Mode	Mode of stop (bus, ferry, or train)
	AccessWalk	Walk time from origin location to stop (min)
	Shelter	Binary variable indicating a sheltered stop
	StopLight	Binary variable indicating an illuminated stop
	StreetLight	Binary variable indicating an illuminated street
	BoardingSlab	Binary variable indicating existence of a boarding slab
	FootPath	Binary variable indicating existence of foot path
	Map	Binary variable indicating existence of printed map/schedule at the stop
Impedance (direct)	FastestTT	Travel time (min) of fastest path to destination from the stop (excluding AccessWalk)
	MinTransfer	Minimum number of transfer among paths from the stop to destination
	MinWalk	Minimum walk time (min) among paths from the stop to destination (excluding AccessWalk)
	MinFare	Minimum fare among paths from the stop to destination(AUD)
Impedance (aggregate)	NumRoutes	Number of available routes from the stop to destination
	TotalFreq	Summation of frequency for all the routes from the stop to destination
	AveTT	Average travel time of all paths from the stop to destination (excluding AccessWalk)
	AveTransfer	Average number of required transfers for all paths from the stop to destination
	AveWalk	Average walking time (min) for all paths from the stop to destination (excluding AccessWalk)
	AveFare	Average fare for all paths from the stop to destination (AUD)
Correction for Correlation	CfC1	Correction for correlation, basic definition
	CfC2	Correction for correlation, weighted by route frequencies
	CfC3	Correction for correlation, weighted by path travel times

Based on this assumption, the application of MNL to model specifications that have interdependencies among the choices may result in inaccuracies in the model estimation. Several researches such as Path Size Logit (PSL), C-Logit and Path Size Correction Logit (PSCL) have been performed in the route choice modelling to overcome the route overlapping problem. One of the practical applicable solutions to this problem for real-sized transport networks is to introduce a correction attribute to fix the systematic utility of the overlapping choices. Reviewing the literature revealed that applying this solution to different cases such as transit models (Lam & Xie, 2002) and intermodal path choice models (Hoogendoorn-Lanser, van Nes, & Bovy, 2005) resulted in significant modelling improvements. The main idea behind applying this correction is to make an approximation of a model with IID errors for the choices by reducing the systematic component of the utilities of the correlated choices.

In this research, the correction factors (CfC1, CfC2, CfC3) are defined based on the Path Size Correction Logit (PSCL) formulation (Bovy, et al., 2008).

As explained in the literature review, the path size correction logit (PSCL) model not only has an advantage to include the random utility theory into the path size factor but also can overcome the computational limitation of the C-logit and PSL models in estimating the correction factors in the real transit networks.

To meet the specifications of the access stop choice model, these correction factors are adjusted for the stop choice model. As a result, these factors are redesigned to adjust the amount of interdependencies among the stops, due to their common routes to the destination.

For this purpose, three definitions of correction for correlation are defined for every stop s in the choice set $C_o^{d,\tau}$. Therefore, these correction factors for an observation from origin location o at departure time τ to destination location d can be defined as:

$$CFC1_s^{d,\tau} = -\sum_{i \in \Gamma_s^{d,\tau}} \frac{1}{\left|\Gamma_s^{d,\tau}\right|} \ln \sum_{t \in C_o^{d,\tau}} \delta_{i,t}^{d,\tau} \qquad (3\text{-}1)$$

$$CFC2_s^{d,\tau} = -\sum_{i \in \Gamma_s^{d,\tau}} \frac{f_{i,s}^{\tau}}{\sum_{j \in \Gamma_s^{d,\tau}} f_{j,s}^{\tau}} \ln \sum_{t \in C_o^{d,\tau}} \delta_{i,t}^{d,\tau} \qquad (3\text{-}2)$$

$$CFC3_s^{d,\tau} = -\sum_{i\in\Gamma_s^{d,\tau}} \frac{(T_{i.d}^{\tau})^{-1}}{\sum_{j\in\Gamma_s^{d,\tau}} (T_{j.d}^{\tau})^{-1}} \ln \sum_{t\in C_o^{d,\tau}} \delta_{i,t}^{d,\tau} \qquad (3\text{-}3)$$

with the following notation:

i, j : Indices of routes

s, t : Indices of stops

$\Gamma_s^{d,\tau}$: Set of all routes at stop s with reasonable paths to the destination d at time τ

$f_{j,s}^{\tau}$: Frequency of route i at stop s at time τ

$T_{i.d}^{\tau}$: Travel time of the fastest path from stop s boarding on route i to destination d at time τ,

$\delta_{i,t}^{d,\tau}$: Stop-route incidence parameter, $\delta_{i,t}^{d,\tau} = \begin{cases} 1, & \text{if } i \in \Gamma_t^{d,\tau} \\ 0, & \text{if } i \notin \Gamma_t^{d,\tau} \end{cases}$

The following example illustrates the logic behind the definition of the $CFC1$ correction factor. Assume there are only two stops p and q that share common routes among all the stops in an example choice set $C_o^{d,\tau}$. Assume that p and q have completely similar sets of routes $(\Gamma_p^{d,\tau} = \Gamma_q^{d,\tau})$. Therefore, we can conclude that $CFC1_p^{d,\tau} = CFC1_q^{d,\tau} = -\ln 2$. One solution for including these factors in the utility of the two stops is to insert this correction value directly into the utility of these stops (fixing the coefficient of the attribute $CFC1$ to *1.0*). In this situation, the utility of stops p and q will be reduced by $\ln 2$. Given the logit expression of probabilities $(p_i = \frac{e^{u_i}}{\sum_j e^{u_j}})$, this reduction in utility decreases the probability of choosing p and q by one-half. This could be a right probability correction if stops p and q are assumed to be similar because they have identical route sets. In that scenario, the coefficient of $CFC1$ could be fixed to *1.0* to guarantee that such stops with identical sets of routes are represented only one time in total. However, that assumption is not necessarily correct. Even if two stops share exactly identical routes, other characteristics such as location or other facility features cause differences between the two stops. Therefore, the coefficient of $CFC1$ should be less than *1.0*, and the ideal approach is to let the model estimate the proper coefficient for these correction terms.

$CFC2$ and $CFC3$ are defined in the same way. The only difference in these correction factors, compared with $CFC1$, is related to the contributions of route overlaps in these correction factors. The corrections factors in $CFC2$ and $CFC3$ are weighted proportional to route importance. These weights are formulated on route frequencies in $CFC2$; in $CFC3$ they are defined based on the inverse of the route best travel time to destination.

The proposed choice model can be considered a hybrid model with a nested logit formulation at the mode level and a corrected logit formulation at the stop level. This proposed structure for the model makes the choice model capable of rectifying two stated issues with the choice models. Firstly, the choice model proposed a nested structure to treat the correlation among the choices of transit modes (e.g. train, bus and ferry). Secondly, the proposed choice model includes a correction attribute to rectify the correlation of the error terms among the stop choices due to route commonalities among the stops (Nassir, Hickman, Malekzadeh, & Irannezhad, 2015). The next section explains the choice set generation algorithm, which has been applied in this research.

3.5 CHOICE SET GENERATION ALGORITHM

The main purpose of developing the choice model in this research is to predict the travellers' access stop choice preferences when travelling from their actual origins, by accounting access walk distances to transit stops, considering different mode(s) (bus, ferry, or train) serving each stop, and being aware of the time-dependent impedances from each stop to the destination.

The proposed choice sets in this research are generated by a transit time-dependent K-shortest path algorithm that generates paths between given O-D pairs with the objective function of minimizing the arrival time to the destination. The proposed algorithm for choice set generation is shown in Figure 3-6.

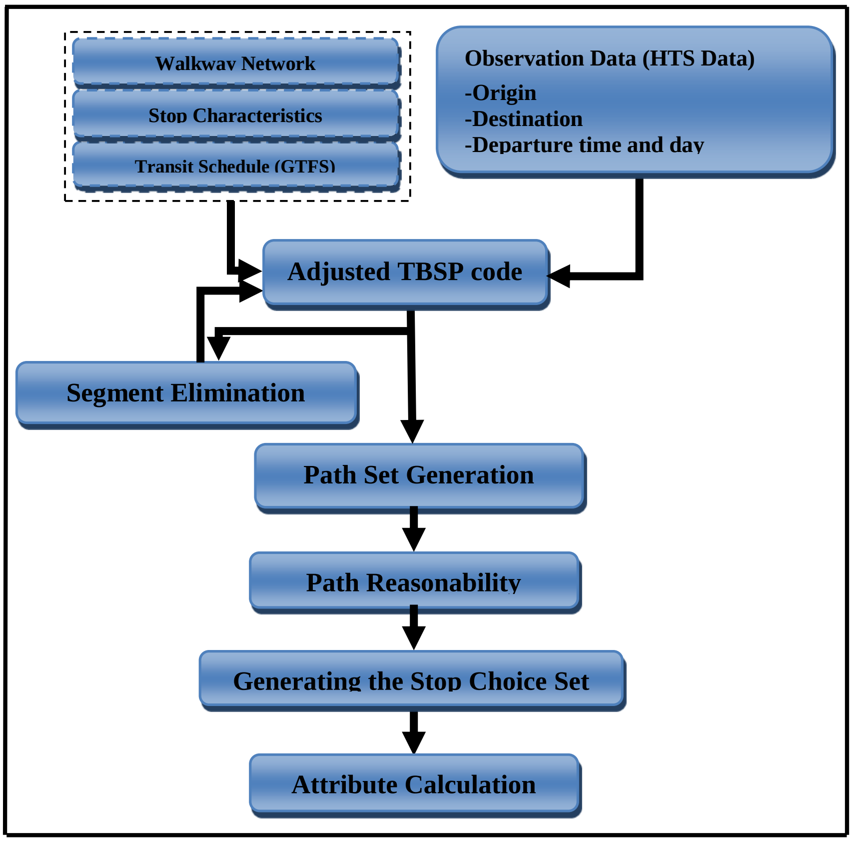


Figure 3-6: Proposed Choice Set Generation Framework

These generated paths include access walks, egress walks, and transfer walks. The choice set of access stops for every observation is generated specific to the locations of origin and destination, and to the time and the day (weekday/weekend/holiday) of the observed travel.

The transit shortest path algorithm used in this research is a version of the transit trip-based shortest path (TBSP) algorithm (Khani, 2013; Khani, Hickman, & Noh, 2014; Khani, Lee, Hickman, Noh, & Nassir, 2012; Nassir, Khani, Hickman, & Noh, 2012; Nassir, Khani, Lee, Noh, & Hickman, 2011) that is modified to terminate after the destination is labelled, to improve the computational efficiency. The original TBSP algorithm is a Dijkstra-type (Dijkstra, 1959) schedule-based shortest path algorithm that with every execution finds the fastest time-dependent transit itineraries from a given origin, at a given time, to all destinations in the network. The advantage of TBSP, compared to other schedule-based transit shortest path algorithms, is that at each labelling stage, all the stops that are served by a given transit trip are labelled together, and only stops that are potential transfer location are afterwards tested for labelling other nodes in the network.

The K-shortest path algorithm is an iterative TBSP calculation with a "segment elimination" module that is executed after each iteration of the TBSP execution. The main difference between the proposed elimination path algorithm and existing link elimination models (Bekhor, et al., 2006; Prato, 2009) is in the definition of the segments to be eliminated. Here, a segment is defined as the combination of a boarding stop, an alighting stop, and a route connecting those two stops. After the TBSP generates a path, all the segments in that path are eliminated in subsequent iterations; meaning that we eliminate the possibility of that exact segment appearing in subsequently generated paths. However, possible variations that overlapping segment could appear in subsequent paths. For example, as shown in Figure 3-7, if a path includes a segment with a boarding at stop *a* on route *i* and an alighting at stop *b*, the segment *a-i-b* is eliminated in the following iterations. However, eliminating *a-i-b* does not prohibit "neighbour" variations of that segment such *a-i-d, a-j-c,* or *d-i-b*. This guarantees diversity in the set of generated paths.

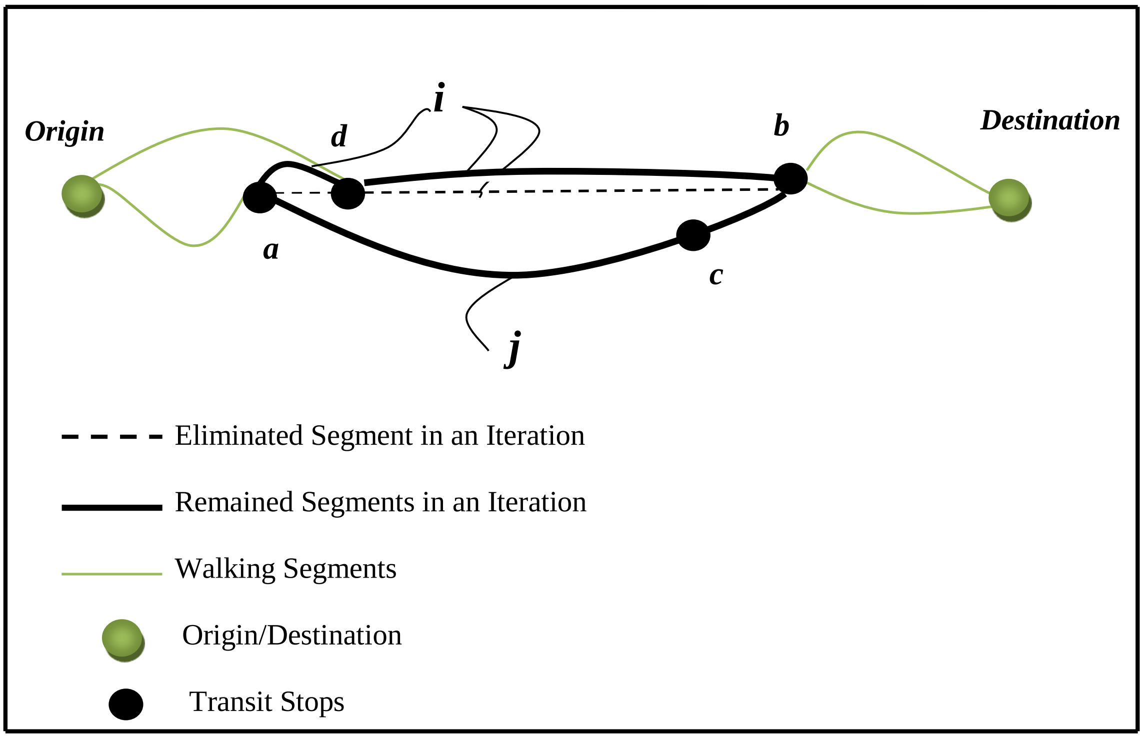


Figure 3-7: Schematic diagram for proposed segment elimination method

As shown in the proposed choice set generation framework (Figure 3-6), a reasonability check needs to be performed on the path, after each path is generated by the TBSP algorithm. The reasonability check passes if the following two conditions hold: 1) the path travel time does not go above the shortest path travel time plus a threshold factor called “off-optimality”, and 2) the number of transfers is limited to three to make the generated choices consistent with the observation in the HTS data (refer to Table 3-1). If the path meets reasonability checks requirement, it will be added to the path set.

The “off-optimality” threshold defined in this reasonability check is set to 20 minutes, is based on the results from previous experimental analysis of the smart card data of SEQ (Nassir.N 2015). These results indicated that the transit users are generally making transit trips with a maximum off-optimality threshold of 20 minutes. As a result, the path generation terminates as soon as a path generated by the K-shortest path code reaches the off-optimality threshold.

Three embedded reasonability criteria are also set in the TBSP shortest path code itself: 1) the transfer walking distance between the transfer stops is limited to 1 km, 2) the access and egress walks cannot exceed 2 km; and, 3) the waiting time before a boarding cannot go above one hour. Therefore, paths that pass the reasonability check automatically holds these three criteria as well.

The embedded limit of 2 km on the access and egress walks in the GIS code guarantees that all the stops are in the walkable range of 2 km. Setting the access and egress walk threshold to 2 km may sound long, but a preliminary analysis on the SEQ household travel survey (HTS) data revealed that the access walk for about 17% of the observations is longer than 1km. This value for egress walk is about 16%. It has also been reported by other researchers that the observed walking distances for transit access and egress in Brisbane (SEQ) are much greater than the values that are conventionally assumed (Burke & Brown, 2007).

Figure 3-8 and figure 3-9 show diagrams of cumulative access and egress walking distances for chosen samples. These figures show a similar pattern in transit users’ behaviour for walking to/from stops. For instance, 61% of travellers walk less than 600 m (10 min walking) to access to transit stops or travel from stops to destinations and 96% of travellers walked less than 1800 m or half an hour for travelling from/to stops.

Figure 3-8: Cumulative walking distance for access to transit stops

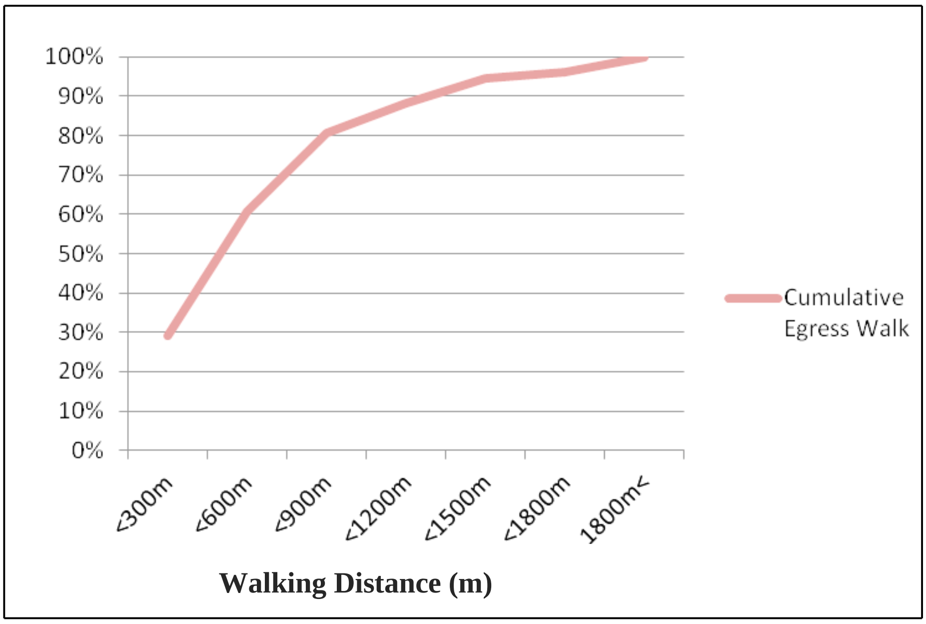


Figure 3-9: Cumulative egress walking distance from transit stops

As shown in Figure 3-8, in the first step, the actual walking distances between stops and origins/destinations on the walking network should be calculated using ArcGIS. These calculated distances are then exported into the proposed shortest path algorithm. An average walking speed of 1.2 m/s was used for the estimation of walking times in this research. Figure 3-10 shows a set of reasonable stops identified within the defined catchment area (2 km) in the network of SEQ.

The set of possible stops are generated by the TBSP algorithm; a reasonability check for acceptable waiting time (one hour) is also performed in this stage. Therefore, a GIS procedure may identify several stops with reasonable access walk but the TBSP algorithm finalizes only a few stops if they can pass the criteria in the reasonability check.

Figure 3-10 shows an example journey in the network of SEQ, with a set of reasonable paths generated by the TBSP algorithm and a set of access stop choices serving these routes. In this example, the generated choice set includes five bus stops, two railway stations, and one ferry terminal serving three bus routes, a ferry route and a train route respectively.

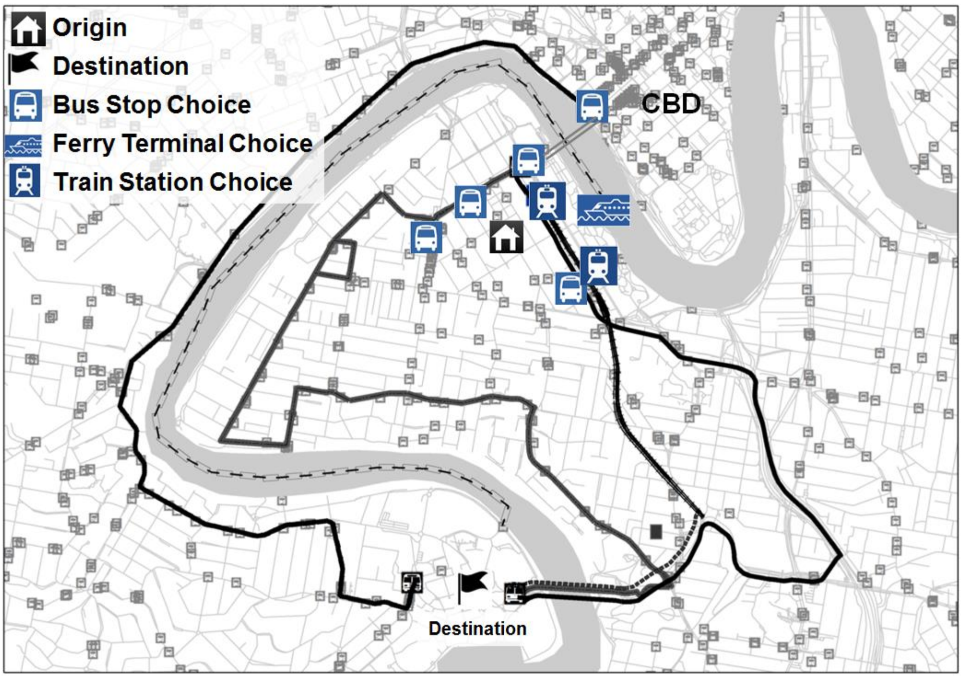


Figure 3-10: Example of Stop Choice Set Generation

As shown in the Figure 3-11, for generating the choice data set in this research, the choice set generation process should be performed for all observed trips between origin and destination (O-D). As a result, each generated choice set should include a chosen (observed) stop and one or more generated stop alternatives (un-chosen stops).

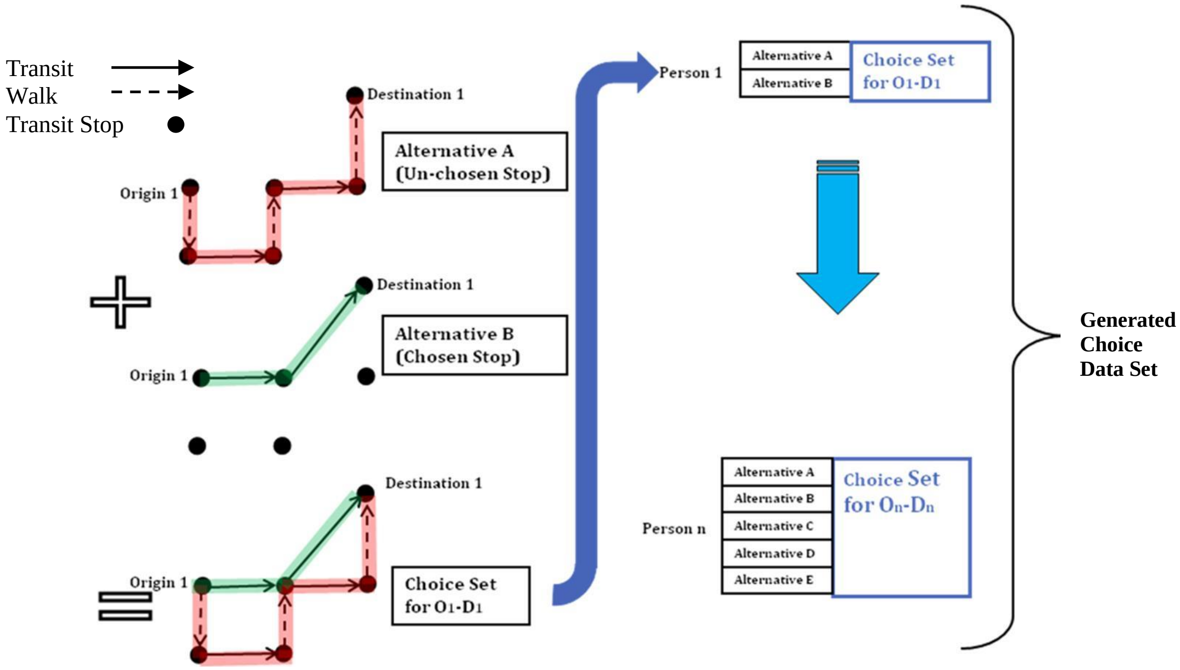


Figure 3-11: A schematic outline for generating the choice data set

3.5.1 Generated choice sets

For about 94.5% (1599 out of 1692) of observations, applying the proposed choice set generation algorithm generated the chosen access stops among the alternatives in the choice set. For the remaining HTS observations, where the chosen stop was not found among the generated choices, that stop was inserted into the choice sets. In order to calculate the impedance attributes for the chosen stops in those cases, a slightly modified K-shortest path generation algorithm was developed that is restricted to starting the path from the chosen alternative. This guaranteed that the chosen stops for all observations are among the choice sets.

Ambiguity in the mapping between the recorded chosen stop locations in HTS and the stop locations in the transit network, led to a small portion of the observations being removed from the analysis. For these ambiguous cases, no stop was confidently matched as the route serving the stop or the mode of the stop was different with the recorded access stop choice in the HTS. To improve the accuracy of the model estimation, 26.8% (455 out of 1692) of these observations were excluded from further analysis.

The set generation algorithm identified between 2 and 70 alternatives for each observation; however, for the majority of observations fewer than 20 stops were generated (refer to figure 3-12).

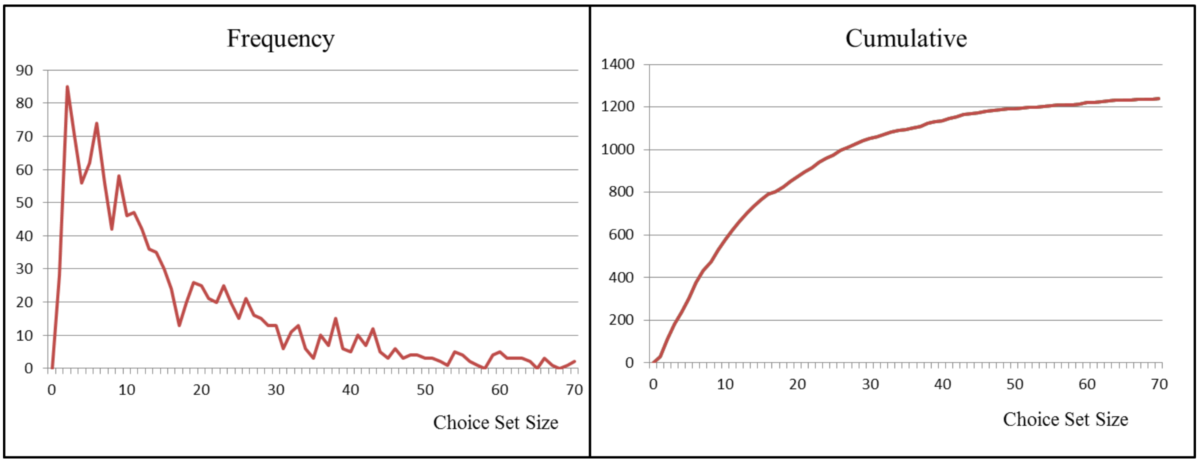


Figure 3-12: Choice Set Size Histograms

As shown in the proposed choice set generation algorithm, after generating the choice sets for all the observations, we need to extract the attributes of these choices for the choice modelling. All these attributes, such as fastest travel time, numbers of transfers, stop amenities attributes are extracted from the choice set in this step.

3.6 CHOICE MODEL CALIBRATION

In this research, the discrete choice estimation software package, BIOGEME, is used to calibrate the access stop choice model. BIerlaire Optimization toolbox for GEV Model Estimation (BIOGEME) is a freeware package for estimating a broad range of random utility models by maximum likelihood approach. It can estimate the logit model, the nested logit model, the cross-nested logit model, and the network MEV model, along with continuous and discrete mixtures of these models (Bierlaire, 2006; Bierlaire & Fetiarison, 2009). Due to the importance of maximum likelihood theory and statistical tests for the discrete choice models, the following sections present a fundamental knowledge about the likelihood theory and its modelling test techniques, prior to explaining the model calibration process.

Maximum Likelihood Estimation Theory

The maximum likelihood method aims to find the optimal model coefficients that maximize the probability of predicting the observed sample of choices correctly.

This method should maximize the likelihood that the sample generated from the model with the chosen coefficients (Koppelman & Bhat, 2006).

The process for maximum likelihood estimation contains two steps. First is to develop a probability function from a given model, for the observed sample. Second is to estimate coefficient values which maximize the likelihood function.

The probabilities of choices for a nested structure based on two modes of transit services can be written as (Koppelman & Bhat, 2006):

$$\Pr(A) = \Pr(A \mid \mathrm{mod}\,1) \times \Pr(\mathrm{mod}\,1 \mid PT) \quad (3\text{-}4)$$

$$\Pr(B) = \Pr(B \mid \mathrm{mod}\,2) \times \Pr(\mathrm{mod}\,2 \mid PT) \quad (3\text{-}5)$$

Where:

$\Pr(A)$: Probability of choosing the alternative "A"
$\Pr(B)$: Probability of choosing the alternative "B"
$\Pr(A \mid \mathrm{mod}\,1)$: Probability of choosing the alternative "A" among mode 1 choices
$\Pr(B \mid \mathrm{mod}\,2)$: Probability of choosing the alternative "B" among mode 2 choices
$\Pr(\mathrm{mod}\,1 \mid PT)$: Mode 1 probability
$\Pr(\mathrm{mod}\,2 \mid PT)$: Mode 2 probability

Probability of choosing an alternative among mode 1 and mode 2 also can be written as:

$$\Pr(A \mid \mathrm{mod}\,1) = \frac{\exp(V_A \times \mu_1)}{\sum_{i \in C_1} \exp(V_i \times \mu_1)} \quad (3\text{-}6)$$

$$\Pr(B \mid \mathrm{mod}\,2) = \frac{\exp(V_B \times \mu_2)}{\sum_{i \in C_2} \exp(V_i \times \mu_2)} \quad (3\text{-}7)$$

Where:

μ_1 : Nest parameter for mode 1
μ_2 : Nest parameter for mode 2

C_1 : Set of all alternatives in mode 1 nest,

C_2 : Set of all alternatives in mode 2 nest,

V_i : Systematic utility of choice i

V_A : Systematic utility of alternative “A” in mode 1 nest,

V_B : Systematic utility of alternative “B” in mode 2 nest,

Probability of modes also can be written as:

$$\Pr(\text{mod}1 \mid PT) = \frac{\exp(\frac{\omega_1}{\mu_1})}{\exp(\frac{\omega_1}{\mu_1}) + \exp(\frac{\omega_2}{\mu_2})} \tag{3-8}$$

$$\Pr(\text{mod}\,2 \mid PT) = \frac{\exp(\frac{\omega_2}{\mu_2})}{\exp(\frac{\omega_1}{\mu_1}) + \exp(\frac{\omega_2}{\mu_2})} \tag{3-9}$$

Hence:

$$\Pr(A) = \frac{\exp(V_A \times \mu_1)}{\sum_{i \in C_1} \exp(V_i \times \mu_1)} \times \frac{\exp(\frac{\omega_1}{\mu_1})}{\exp(\frac{\omega_1}{\mu_1}) + \exp(\frac{\omega_2}{\mu_2})} \tag{3-10}$$

$$\Pr(B) = \frac{\exp(V_B \times \mu_2)}{\sum_{i \in C_2} \exp(V_i \times \mu_2)} \times \frac{\exp(\frac{\omega_2}{\mu_2})}{\exp(\frac{\omega_1}{\mu_1}) + \exp(\frac{\omega_2}{\mu_2})} \tag{3-11}$$

Where ω_1 and ω_2 are the logsum values for the mode 1 nest and the mode 2 nest respectively and they can be written as:

$$\omega_1 = \ln \sum_{i \in C_1} \exp(\mu_1 \times V_i) \tag{3-12}$$

$$\omega_2 = \ln \sum_{i \in C_2} \exp(\mu_2 \times V_i) \tag{3-13}$$

The likelihood function for a sample of ‘O’ individuals with ‘I’ alternatives is defined as follows (Koppelman & Bhat, 2006; Kremelberg, 2010):

$$L(\beta) = \prod_{\forall o \in O} \prod_{\forall i \in I} (P_{oi}(\beta))^{\delta_{io}} \tag{3-14}$$

Where δ^{io} is the incident factor that equals to 1 if alternative i is chosen by individual 0 ; otherwise it equals 0

And P_{oi} is defined as the probability that individual 0 chooses alternative i

For computational purposes, instead of optimising $L(\beta)$ directly, the logarithm function, which is strictly increasing, can be applied. The log-likelihood function for the optimisation would be calculated as follows:

$$LL(\beta) = Log(L(\beta)) = \sum_{\forall o \in O} \sum_{\forall i \in I} \delta_{io} \times \ln(P_{oi}(\beta)) \tag{3-15}$$

It is proven that this log-likelihood expression is a concave function of the coefficients β ; therefore, the optimal values of the β coefficients are the root of the first derivative function of the log-likelihood with respect to β . This derivative function is easily calculated and the Newton Method can be effectively applied to find its root (Koppelman & Bhat, 2006; Kremelberg, 2010).

Hence, the log-likelihood function for the nested logit can be written as:

$$LL(\beta) = Log(L(\beta)) = \sum_{\forall o \in O} [\sum_{\forall i \in C_1} \delta_{io} \times \ln(\Pr\ (A)) + \sum_{\forall i \in C_2} \delta_{io} \times \ln(\Pr\ (B))] \tag{3-16}$$

Statistical Model Tests

Test of Individual Attributes (t-test or t-statistics)

One of the common statistical methods to test the significance of the estimated values of attribute coefficients in the model is the t-statistics method. This statistical technique, in which the standard error of estimation is applied to test whether a particular coefficient is equal to a hypothesized value, takes the following form (Koppelman & Bhat, 2006; Limentani, Ringo, Ye, Bergquist, & MCSorley, 2005):

$$t - test = \frac{\hat{\beta}_k - \beta_k^{*}}{S_k} \tag{3-17}$$

where:

$\hat{\beta}_k$ is the estimated value for the kth parameter,

β_k^* is the hypothesized value for the kth parameter

S_k is the standard error of the estimate

The large absolute values of the t-statistics lead to rejection of the null hypothesis that the coefficient of attribute is equal to the initial hypothesized value. Generally, the majority of statistical software packages assume that hypothesized value β_k^* is zero. The rejection of this null hypothesis means that the estimated value for the coefficient of attribute has a significant effect on the model and it should be kept in the model. On the other hand, low absolute values of the t-statistics means that the attribute does not contribute significantly to the model and can be removed from the model. The critical value for the t-statistics depends on the level of confidence which the analyst needs to test his/her hypotheses (Koppelman & Bhat, 2006; Limentani, et al., 2005):

The level of confidence for testing the hypotheses depends on the value of the t-statistic test. The critical t-values rise with the increasing the levels of confidence. Having attributes with levels of confidence above 90% usually implies that they contribute significantly to the model; attributes with levels of confidence less than 90% can be rejected from the modelling (Koppelman & Bhat, 2006; Limentani, et al., 2005).

Overall Goodness-of-Fit Measures

The rho-squared value is designed on the correlation between the log-likelihood values to measure the overall goodness of fit. The rho-squared values shows the ratio of the distance between the reference model and the estimated model divided by the difference between the reference model and a perfect model. A value of zero indicates that the model cannot estimate better than the reference model, while a value of one shows a perfect model. The rho-squared value can be defined as:

$$\rho^2 = \frac{LL(\widehat{\beta}) - LL(0)}{LL(*) - LL(0)} \qquad (3\text{-}18)$$

In this equation, *LL(0)* shows the log-likelihood with zero value coefficients and represents the log-likelihood for the constants-only model. In other words, *LL(0)* is equal to a situation which there is an equal likelihood of choosing each available alternative. *LL(β^)* shows the log-likelihood for the estimated model; *LL(*)* represents the log-likelihood for the perfect prediction model and it equals zero (Koppelman & Bhat, 2006; Kremelberg, 2010).

Therefore, the rho square can be written as:

$$\rho^2 = 1 - \frac{LL(\widehat{\beta})}{LL(0)} \tag{3-19}$$

Another indicator that shows how data can be fitted to the model is the adjusted rho-squared value. Generally the rho-squared measures have two drawbacks. First, there are no guidelines or scale for a "good" rho-squared value. In other words, the measure cannot assess the quality of an estimated model properly. Second, the rho-squared measures are improved independently of the importance of the variables added to the model. To rectify these limitations, the rho-squared factor is replaced by an adjusted rho-square measure that takes the number of degrees of freedom used in the model into account (Koppelman & Bhat, 2006).

Test of Entire Model

In statistics, to compare the fit of two models when one of them is null model, a likelihood ratio test is applied. This test shows whether a model fit is improved as result of adding one or more attributes to the model.

The test statistic "D" is twice the difference in these log-likelihoods and can be written as follows:

$$D = -2(LL(0) - LL(\beta)) \tag{3-20}$$

This test-statistic has an approximately chi-squared (χ^2) distribution with degrees of freedom equal to $df0 - df\beta$ which represents the differences between the number of attributes of base model and the model needs to be tested.

The level of confidence can be calculated based on critical Chi-Squared (χ2) values for a range of degrees of freedom. As with the critical values for t-test, the rejection or acceptation of the model is a matter of judgment: generally, models with levels of confidence over 90% can be acceptable (Koppelman & Bhat, 2006; Limentani, et al., 2005).

3.6.1 Model calibration results

As noted earlier, a small portion of the observations were excluded from the analysis, due to uncertainties and ambiguities in the mapping between the chosen stops and the choice set in the HTS data. Therefore, the total observed travel records which are extracted from HTS data and used in this research were 1237 observations. As explained previously, for validation purposes, the dataset also is split by using SPSS (Ver.16). As a result, 80% (990 out of 1237) of the records being randomly selected for the calibration dataset, and kept the remaining 20% (247 out of 1237) of observations to validate the model.

Preliminary analysis indicated that using a nested logit structure choice model with nests defined as modes of transit would significantly improve the model fit from ρ^2=0.244 to ρ^2=0.296. The results of MNL model presented in Table 3-5. As shown in this table although the Independency of Irrelevant Alternatives (IIA) assumption in the MNL models makes the model estimation easier, the model fit is significantly lower than the model fit in the adopted nested structure (NL) models.

However, as explained earlier, initial investigation on the nested structure of choice model with nests defined as “bus”, “train”, and “ferry” revealed that the nesting parameters (estimated nesting coefficients) were not estimated to be significant for the two nests “train” and “ferry”. Therefore, alternative nesting structures were tested and the nesting structure of “train” and “not-train” was chosen in this research. This nesting structure provides the best model fit and statistically significant attributes for the utility function.

The choice model calibrated for different combination of attributes, using the defined nesting structure and the described correction factors for rectifying the overlaps (CFCs). The best results for different combination of attributes reported in Table 3-5.

The t-statistics in the output of choice model indicate that there is a significant correlation (at the 0.01 level) in the choices of mode “train” and also in the choices of mode “no-train”. The coefficients of attributes CfC1 and CfC3, which explain the correlation among the routes, are found to be significant at the 0.05 level.

Table 3-5: Choice Model Estimation Results

Name of Model		**MNL**	**M0**	**M1**	**M2**	**M3**
Number of observations		990	990	990	990	990
Initial log-likelihood		-2091.52	-2091.52	-2064.65	-2068.65	-2061.61
Final log-likelihood		-1788.026	-1665.04	-1662.33	-1662.73	-1662.11
Likelihood ratio test		1153.385	1399.35	1404.79	1403.97	1405.224
ρ^2		0.244	0.296	0.297	0.297	0.297
Adjusted ρ^2		0.242	0.293	0.294	0.293	0.294
Utility Parameters	AccessWalk	-0.211 (-22.71)**	-0.0518 -0.00816	-0.0574 (-5.70)**	-0.0568 (-5.69)**	-0.0577 (-5.71)**
	FastestTT	-0.0394 (-7.01)**	-0.00712 (-3.81)**	-0.00816 (-3.86) **	-0.00806 (-3.85) **	-0.00822 (-3.86) **
	MinTransfer	-1.1 (-14.24)**	-0.213 (-4.93)**	-0.253 (-4.82) **	-0.249 (-4.81) **	-0.255 (-4.82)**
	NumRoutes	0.102 (6.99) **	0.0206 (3.86) **	0.0211 (3.72) **	0.0210 (3.74) **	0.0211 (3.72) **
	Shelter	0.703 (8.48)**	0.0466 (1.93)	0.0566 (2.03)*	0.0550 (2.01)*	0.0571 (2.04) *
	CfC1	-	-	0.0538 (-2.00)*	-	-
	CfC2	-	-	-	0.0485 (-1.88)	-
	CfC3	-	-	-	-	0.0563 (-2.07)*
Nests	Train	-	4.79 (3.91) **	4.15 (3.78) **	4.21 (3.79) **	4.12 (3.77) **
	No_train	-	4.60 (5.89) **	4.12 (5.87) **	4.17 (5.86) **	4.10 (5.88) **

** Significant at 0.01 level
* Significant at 0.05 level

Comparing these models shows that choice model M3 (with a correction factor based on the inverse of the fastest travel time) presents the best final log-likelihood (-1662.11) among the models. To confirm the level of choice model M3 improvement, compared to the base model M0 (the model without correction factor), a likelihood ratio test is applied.

As explained before, the likelihood ratio test can be calculated as follows:

$$D = -2(LL(0) - LL(\beta)) \quad (3\text{-}20)$$

Hence:

$$D = -2(-1665.042 - (-1662.107))$$

$$D = 5.87$$

Therefore the likelihood ratio can be calculated based on the differential degrees of freedom between the M3 and M0 models, the test statistic “D” and the critical Chi-Squared ($\chi 2$) values. The likelihood ratio test outcome indicates significance improvement at the P=0.05 level, the result of adding the correction term CfC3 to the model in this research.

It also shown in the table 3-5, attributes of AccessWalk (walk time from origin location to access stop), FastestTT (travel time of fastest path to destination from the access stop), MinTransfer (minimum number of transfer among paths from the stop to destination), NumRoutes (number of reasonable routes from the access stop to destination) and Shelter availability are significant in all four models. The coefficients are almost similar in all four models and the signs of all coefficients are as expected. The magnitude of the CfC3 coefficient, similar to CfC1 and CfC2, is estimated to be consistent with the assumptions specified in the model specification section. The magnitudes of all estimated coefficients are smaller than 0.06 which confirms our initial assumption (a proper coefficient should be smaller than 1).

The results of the model calibration, however, indicate that the fare is not a significant attribute in the developed choice model. This issue results from the zone-based structure of the transit fares in SEQ, which share similar fare values to all access options in the choice set for travelling between the OD pair. As a result, travellers’ sensitivities to fares could not be captured in the choice model. This issue will be discussed more in the next chapter, where a solution will be proposed to overcome the model limitation. The outcome of the model calibration revealed that the perception of users in regarding to similarities among the stop choices is not highly affected by the routes serving the stops, but is probably more affected by the mode of the stop.

Reviewing the coefficients of choice model M3 shows that when an average person is choosing an access stop, every minute of access walk is equivalent to about 7 minutes of travel time from the departure stop (i.e. the rate of substitution is about 7). The considerable magnitude of access walk (-0.0577) can be interpreted in two ways: 1) the act of walking has a high disutility; or, 2) a myopic behaviour exists in the choice of access stop, as people may have a preference for arriving at the access stop faster, in spite of travelling faster to their destination by walking to a farther stop. This interpretation could prove the limitations of human rationality and travellers' judgement in using public transport, as reviewed in the transit route assignment techniques in Chapter 2.

Another attribute which is significant in the results of the choice model is MinTransfer. The coefficient of MinTransfer is large in all models, in comparison with FastestTT (about 31 times) and even to AccessWalk (4.4 times). These results show a high disutility perceived by transit users for the access stops that have no direct routes to the destination. Therefore, these results can be interpreted that generally people prefer to walk more, and also to spend more time in travel, at least in the expected travel time, in order to start their trip from a stop that has a more direct connection (non-stop routes) to their destination.

The modelling results also revealed that the availability of shelter is found to be significant. This outcome indicates that transit users generally prefer to walk about one minute more to find a stop with shelter. Reviewing the rate of substitutions among the coefficients reveals that, an average, travellers tend to travel about seven minutes more to find a sheltered stop. This result can be interpreted that the stop choice for access to the transit network is significantly affected by the attributes related to the stop itself. These results confirm the need of more realistic behavioural analysis of the passengers, for more accurate planning and policy analysis.

Another remarkable observation in this research is NumRoutes. As shown in Table 3-5, number of routes is found to be significant at level of 0.01. This can be interpreted that travellers choose the stops based on the number of available routes from the stop to their destination. In other words, transit users give a positive value for the stops that have multiple reasonable route choices to the destination. This could relate to the value of having a back-up plan in case of disruption of service or a long delay on one route.

These results again support modelling the choice model at the level of stop; they also confirm the importance of utilising the transit choice models that are based on path strategies as these stop related attributes, such as AccessWalk, Shelter and NumRoutes, are usually neglected in conventional planning and operational models.

An Example of Travellers' Disutility Perception

Table 3-6 presents a better sense of the results of the choice model calibration, showing three different possible scenarios with identical disutility values for transit users to choose their paths to a destination. In this example, the estimated disutility is based on the assumption that the routes passing the stops do not have any overlaps with each other. It is assumed that the transit users have access to only one stop, either bus/ferry or train only. Consequently, based on the results of the model calibration, transit users should have equally likely to choose any of these alternatives.

Table 3-6: An example for stops choice alternatives with similar disutility values

Alternatives / Attributes	Alternative "A"	Alternative "B"	Alternative "C"
AccessWalk(min)	4	6	9
FastestTT(min)	23	41	50
MinTransfer	2	1	0
NumRoutes	2	2	2
Shelter	Available	Available	Available

As highlighted in this example, travellers' perception regarding alternative (stop) "A", with 23 min FastestTT, 4 min AccessWalk and two MinTransfer, should be similar with stop "B", with 41 min FastestTT, 6 min AccessWalk and one MinTransfer, and also with stop "C", with 50 min FastestTT, 9 min AccessWalk and without any transfer. Comparing these choices can emphasize the importance of the number of transfers and access walk to transit stops among the travellers and can provide a better understanding about travellers' behaviour and their perception about the transit system.

To summarise the outcome of the choice model calibration, we can conclude that MinTransfer has the highest importance among transit users in their perception about the transit network. After number of transfers, the access walk to stops has significant magnitude in the perception of transit users when they choose their stop or route to destination. Following these attributes, shelter availability and number of reasonable routes departing from the access stop to destination are found to be other significant factors among transit users.

3.7 TRAVELLERS' SUBJECTIVITIES IN PERCEPTION OF TRANSIT NETWORK

As explained earlier, one of the drawbacks in the existing accessibility approaches is related to their limitation for capturing the subjectivity of travellers in perceptions of the transit network. To have a better understanding about the transit users' subjectivity, we examined observed strategic choices of travellers in the case study (990 observed transit travels). This investigation also utilised the same generated (unchosen) dataset which we employed for the choice model calibration. The results of transit users' strategic choices are summarized in Figure 3-13.

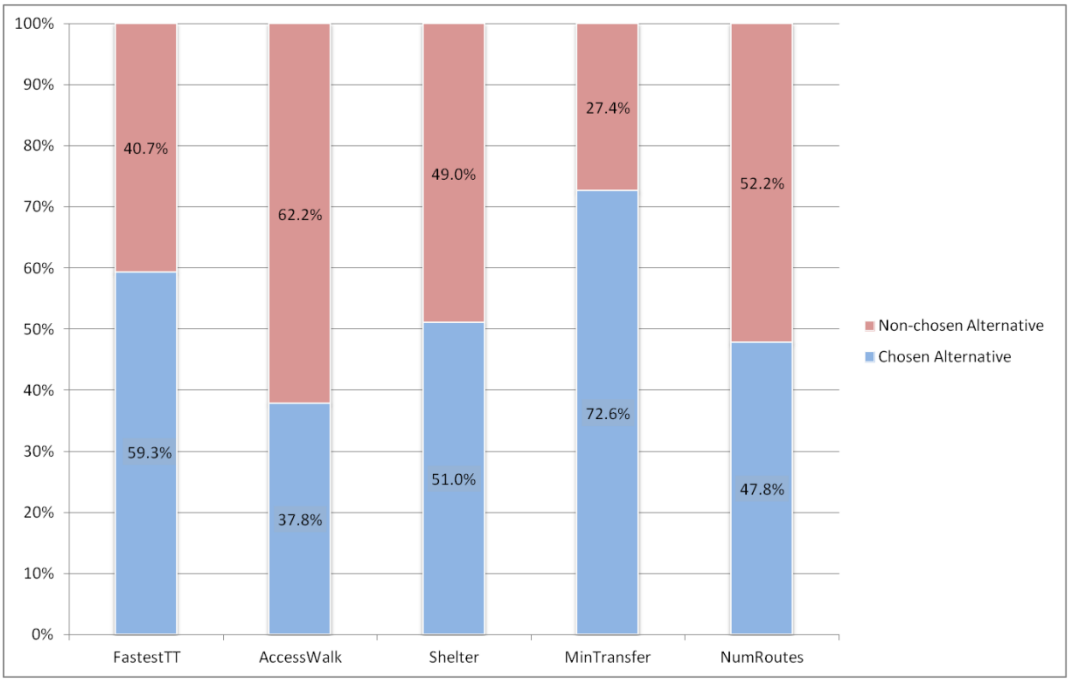


Figure 3-13: Share of Travellers' Subjective Choices

As shown in above bar graph, transit users demonstrate different strategies for choosing the access stop in their transit journey. Among the attributes which have been found significant in the choice model calibration, choosing a stop with the most direct path to the destination has the highest preferences among the passengers. However, these results indicated that still 27.4% of passengers did not choose the path with minimum transfer to their destinations and they may have other preferences in travel through the transit network.

Choosing the access stop with fastest travel time to destination (from access stop) is another travellers' choice which has almost high desirability among choices.

However, again about 40.7% of transit users did not choose the stop with fastest travel time from access stop to destination.

Also, it was shown that about 51% of transit users preferred to board public transport from a stop which is equipped with the shelter. It should be noted that only in 13% of these cases, all the stops in the choice set are equipped with shelter.

In addition, 47.8% of passengers chose the stops with the highest number of routes to destination and about 37.8% transit users preferred to walk to nearest stop for boarding public transport.

To highlight the transit users' subjectivity to travel time attributes and stop attributes, the travel time attributes (AccessWalk and Fastest TT) and also the stop attributes (Shelter and NumRoutes) are combined together and the results of travellers' subjectivity for these combined attributes are summarised in Figure 3-16. The combined attribute for travel time indicated the subjectivity of transit users to total travel time from origin to destination. As shown in this figure, only 29% of travellers chose the alternatives with fastest travel time to destination (from origin). These outcomes underline that transit users have various preferences in the transit network other than only travel time to destination. This observation is very important while traditional accessibility models only focus on computing the travel time for the accessibility estimation and they ignore the travellers' preferences and their subjectivity in perception of transit network.

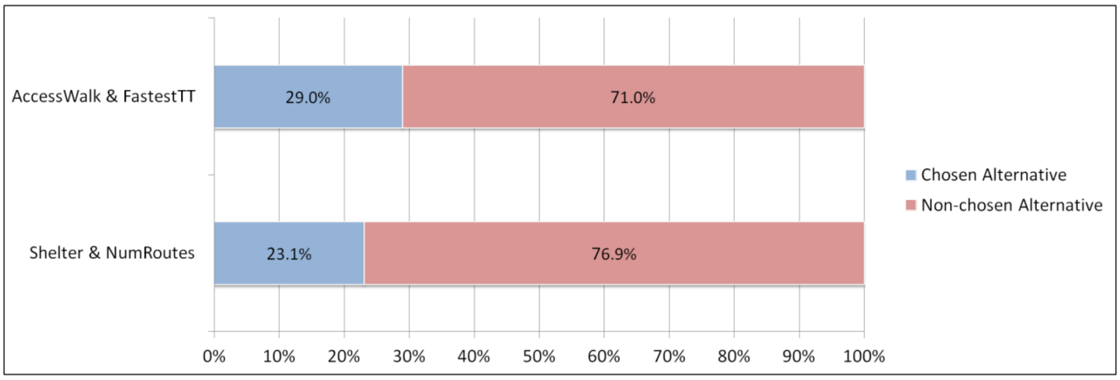


Figure 3-14: Share of Travellers' Subjective Choice for the Combined Attributes

Figure 3-14 also highlights that about 23.1% of transit users choose the stops because of the attributes associated to the stop itself. It should be noted that only in

38% of these cases, the chosen stops (with the highest number of available routes and shelter) have the fastest travel time to destination.

For further clarification about travellers' subjectivities and their stochasticity in the transit network, it is also important to investigate:

- Whether all transit users choose the alternatives based on the highest utility of attributes?
- How the route probability estimations can predict the travellers' route choice behaviour in the transit network?

To answer these questions, the utility and probability of chosen and non-chosen alternatives need to be estimated. The systematic utilities can be calculated based on parameters of Table 3-5 and the probabilities of choices in the developed nested structure can be written as (Koppelman & Bhat, 2006):

$$\Pr(A) = \Pr(A/train) \times \Pr(train/PT) \qquad (3\text{-}21)$$

$$\Pr(B) = \Pr(B/no-train) \times \Pr(no-train/PT) \qquad (3\text{-}22)$$

Where:

$\Pr(A)$: Probability of choosing the alternative "A" (for the train access stops)

$\Pr(B)$: Probability of choosing the alternative "B" (for the no-train access stops)

$\Pr(A/train)$: Probability of choosing the alternative "A" among train stop choices

$\Pr(B/no-train)$: Probability of choosing the alternative "B" among no-train stop choices

$\Pr(train/PT)$: Train mode probability

$\Pr(no-train/PT)$: No-train mode probability

Probability of choosing an alternative among train and no-train stop choices also can be written as:

$$\Pr(A/train) = \frac{\exp(V_A \times \mu_T)}{\sum_{i \in C_T} \exp(V_i \times \mu_T)} \qquad (3\text{-}23)$$

$$\Pr(B / no-train) = \frac{\exp(V_B \times \mu_{NT})}{\sum_{i \in C_{NT}} \exp(V_i \times \mu_{NT})} \tag{3-24}$$

Where:

μ_T : Nest parameter for "train" nest ($1< \mu_T = 4.12$)

μ_{NT} : Nest parameter for "no-train" nest ($1< \mu_{NT} = 4.10$)

C_T : Set of all alternatives in "train" nest,

C_{NT} : Set of all alternatives in "no-train" nest,

V_i : Systematic utility of choice i

V_A : Systematic utility of alternative "A" in "train" nest,

V_B : Systematic utility of alternative "B" in "no-train" nest,

The systematic utility is a deterministic or observable part of the utility model which is a function of the attributes of the alternative. As a result, systematic utilities can be calculated based on estimated parameters for the choice model attributes and probability of train and no-train modes also can be written as (Koppelman & Bhat, 2006):

$$\Pr(train / PT) = \frac{\exp(\frac{\omega_T}{\mu_T})}{\exp(\frac{\omega_T}{\mu_T}) + \exp(\frac{\omega_{NT}}{\mu_{NT}})} \tag{3-25}$$

$$\Pr(no-train / PT) = \frac{\exp(\frac{\omega_{NT}}{\mu_{NT}})}{\exp(\frac{\omega_T}{\mu_T}) + \exp(\frac{\omega_{NT}}{\mu_{NT}})} \tag{3-26}$$

Where ω_T and ω_{NT} are the logsum values for the "train" nest and the "no-train" nest respectively and they can be written as:

$$\omega_T = \ln \sum_{i \in C_T} \exp(\mu_T \times V_i) \tag{3-27}$$

$$\omega_{NT} = \ln \sum_{i \in C_{NT}} \exp(\mu_{NT} \times V_i) \qquad (3\text{-}28)$$

Figure 3-15 presents the travellers' choices for the 25 available options in decreasing utility order. According to these results, about 43% of transit users chose the paths with the highest utility in the network. Although, we can observe a general decline in the chance of choosing the paths with lower estimated utilities (higher rank), around 28% of travellers chose alternatives which are ranked 4^{th} or higher in the utility calculation.

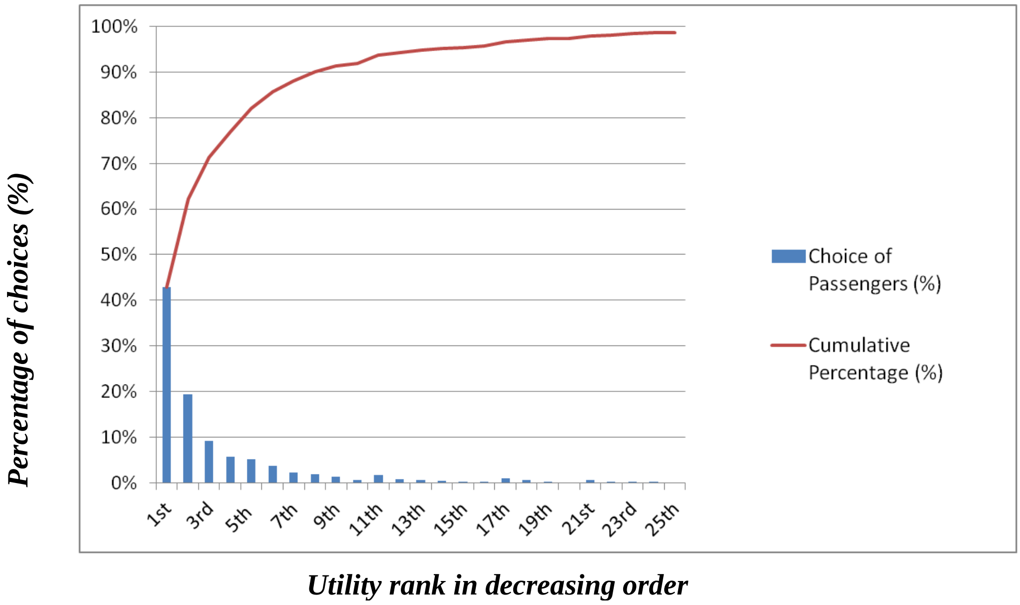


Figure 3-15: Choice of Alternatives in Decreasing Utility Order

The results of the travellers' choices for the 25 available options in decreasing probability order also is summarised in Figure 3-16. The outcome of this observation revealed that about 49.6% of travellers chose the path with maximum probability and similar to the graph for the utility estimation, we can observe a general decline in likelihood of choosing the alternatives with lower estimated probability. However, again in many cases (about 22.5%), travellers chose alternatives with rank 4^{th} or higher in terms of estimated probability.

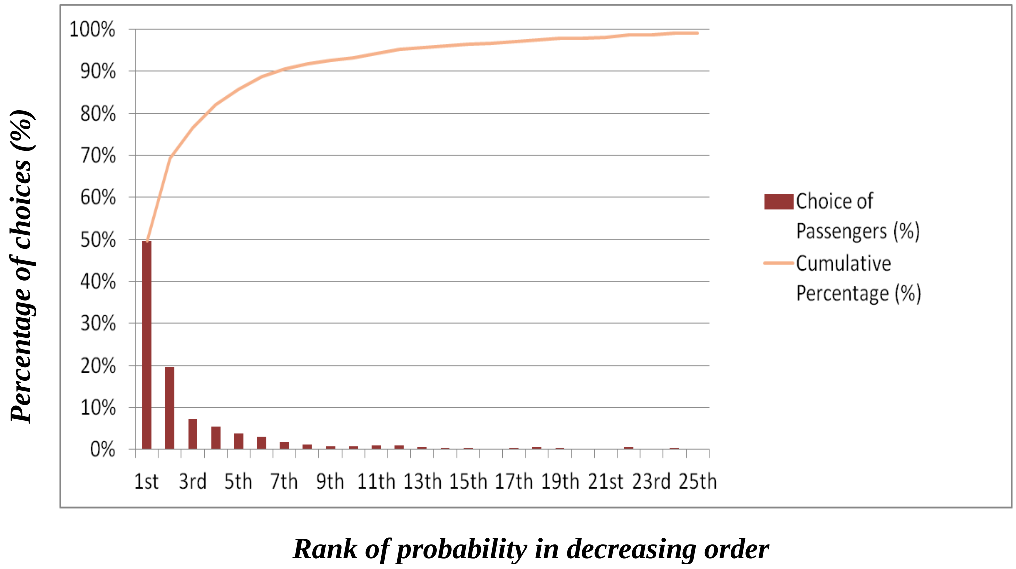


Figure 3-16: Choice of Alternatives in Decreasing Probability Order

These results again can confirm the stochasticity and subjectivity of travellers in the perception of transit network and also highlight that why existing approaches based on shortest travel time or even maximum estimated utility cannot measure the accessibility accurately. Different travellers have various preferences in the transit network which lead them to choose different paths in different situations. Also, considering that all travellers have perfect knowledge of the network and they can find the best route to the destination can be a strong assumption.

As an example, Figure 3-17 demonstrates a real example for a traveller's observed choice behaviour in the transit network. As shown in this actual sample from HTS data set, the observed transit user chose the path which is ranked third in the choice set (between four available options) opposing to choose the path with the highest estimated utility (-1.036) or the highest estimated probability (0.537).

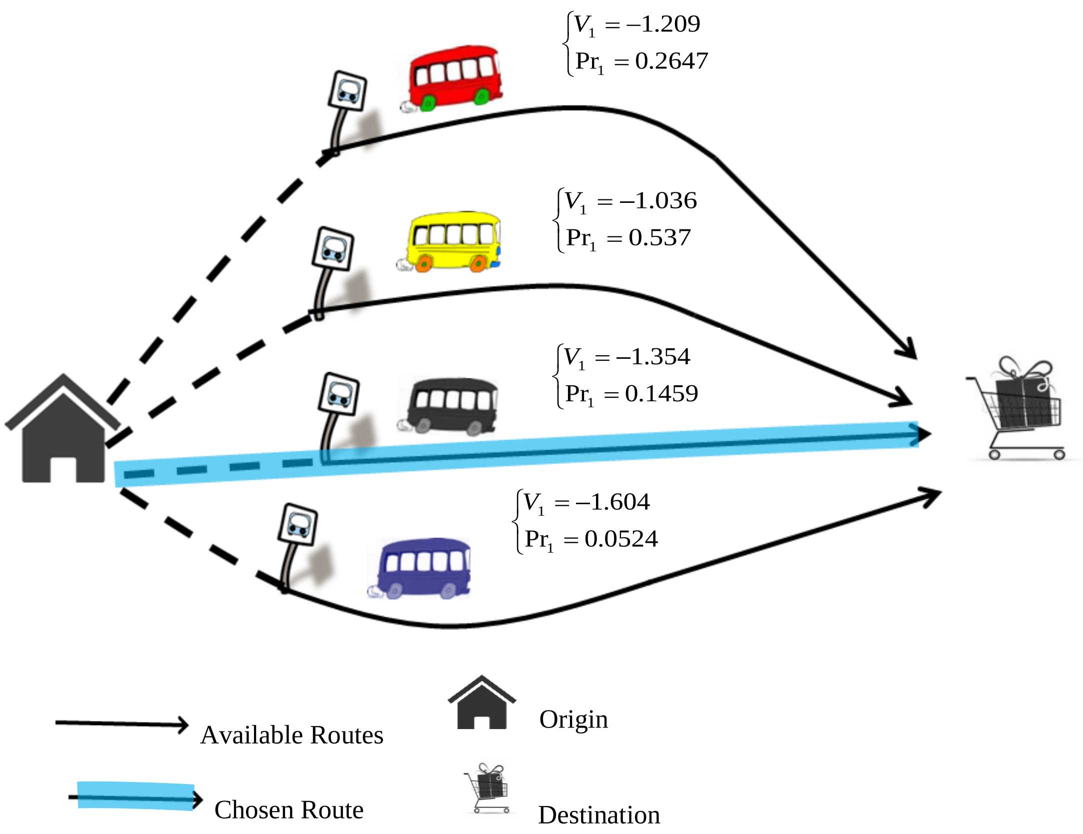


Figure 3-17: An example for observed and alternative choices

To capture these stochastisities and subjectivities which are confirmed to exist in the transit users' perception, this research proposed an algorithm to apply global set of reasonable access stop choices for the accessibility estimation as well as the choice model calibration. The proposed approach for the choice model calibration was explained in this chapter and the proposed approach for accessibility estimation based on universal set of available options will be discussed in the Chapter 4.

3.8 MODEL VALIDATION

As stated in the modelling framework, to test the validity and reliability of calibrated model, a validation test is carried out in this research work. For this purpose, 20% (247 out of 1237) of randomly selected observations remained to validate the model. In order to validate the calibration results, the preferred calibration model (M3 model) needs to be applied to the validation data set. Applying the M3 model coefficients to the validation data set means that the likelihood values and model fit (rho-square) can be calculated for the independent validation data set. These values for the control model should be plotted against the calibrated model to check how well M3 model can simulate the validation data set. Figure 3-18 shows an algorithm for the model validation procedure.

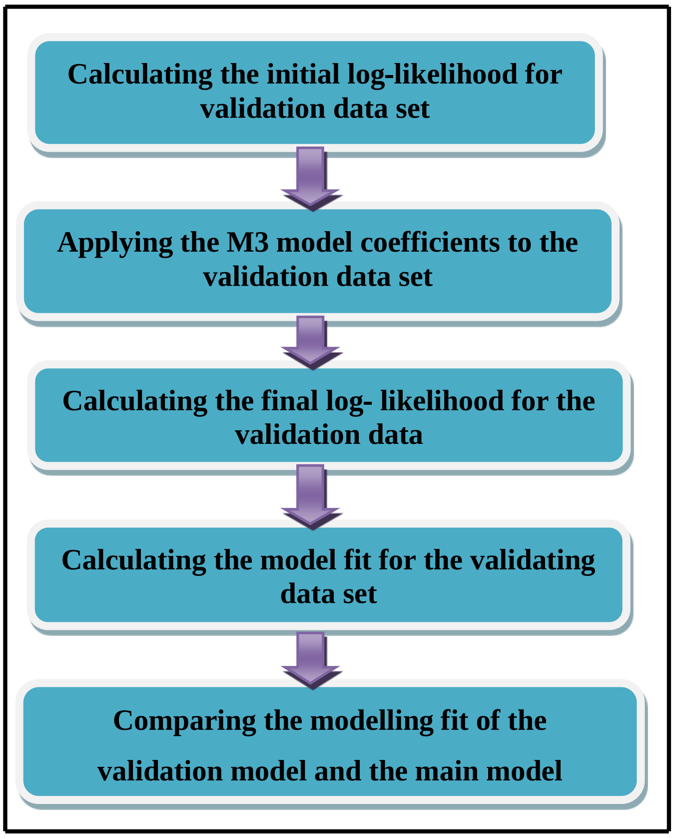


Figure 3-18: Model Validation Algorithm

For this purpose, in the first step the initial log-likelihood for the validation data set needs to be calculated. Initial log-likelihood calculation is based on the assumption that the modeller does not have any preference or knowledge about the choices and therefore the chance of choosing an alternative can be defined by a probability equation. Therefore, the initial log-likelihood can be written as follows:

$$LL(0) = \sum_{\forall o \in O} \sum_{\forall i \in I} \delta_{io} \times \ln(P_{oi}(0)) \qquad (3\text{-}29)$$

where i represents available alternatives for individual o.

Therefore, in this research the initial log-likelihood for validation dataset is estimated:

$$LL(0) = -608.33$$

By applying the attributes' coefficient of model M3 to the validation dataset, the final log- likelihood for the validation dataset can be estimated as follows:

$$LL(\beta) = \sum_{\forall o \in O} [\sum_{\forall i \in C_1} \delta_{io} \times \ln(\Pr\ (A)) + \sum_{\forall i \in C_2} \delta_{io} \times \ln(\Pr\ (B))] = -426.31$$

As noted, to validate the calibrated model, we need to confirm that the calculated coefficients for the M3 model can improve the model goodness-of-fit for the validation data set. The model fit for validation data set can be calculated as:

$$\rho^2 = 1 - \frac{LL(\hat{\beta})}{LL(0)} \qquad (3\text{-}19)$$

Hence: $\rho^2 = 1 - \frac{-426.31}{-608.33} = 0.2995$

As summarised in table 3-7, this validation confirms the explanatory power of the estimated model at the level of ρ2=0.297. Accordingly, the results of model fit with the independent datasets can prove and confirm the reliability of the estimated coefficients in the M3 model.

Table 3-7: Model fit results of calibrated model and validated model

	Number of observations	Initial log-likelihood	Final log-likelihood	ρ2
Main Model	990	-2061.61	-1662.11	0.297
Control Model	247	-608.33	-426.31	0.2995

3.9 CONCLUSION

The developed discrete choice model in this research revealed several theoretical advantages and valuable outcomes. First, the developed choice model at stop level solves the modelling difficulties with passengers' strategic boarding/alighting behaviour in high frequency transit network and it also provides a platform to capture the benefits of transit network diversity to travellers (see further in Chapter 4).

Second, the proposed stop choice framework allows us to capture the behavioural aspects of transit users and the spatio-temporal characteristics of transit system, which cannot be captured at the level of path choice. The results of the choice model revealed that the choice of access stop is affected not only by the attributes of impedance from the stop to the destination, but also, significantly, by the attributes of the stop itself, such as access walk to stops. These results also revealed that, contrary to conventional assumptions in the transit accessibility estimations, the transit users' behaviour is significantly affected by attributes other than the travel time, such as minimum number of transfers, number of available paths at the access stop and shelter availability.

Adding these attributes to the definition of utility can highly improve the accuracy of accessibility measurement. While the goal of an effective accessibility measure is to quantify the perceptions of passengers in accessing urban facilities, a behaviour-based utility model can be a very helpful tool to incorporate actual passengers' perceptions when using the transit network.

Third, the proposed choice model has effectively treated the problem of correlation among the alternatives and also among the transit modes by coupling the correlation correction factor in a nested logit structure.

Forth, investigating on travellers' choice behaviour also confirmed the transit users' subjectivity and stochasticity in perception of transit network. These results revealed that over 57% of travellers did not choose the path with the highest estimated utility and also over 50% of transit users did not choose the path with the highest estimated probability in the choice set. To capture these subjectivities, the developed model not only used global set of reasonable access stop choices for the choice model calibration but also, it is proposed to use this universal set of available choices for the accessibility estimation. This proposed approach for accessibility estimation will be discussed in the next chapter.

Summary of the chapter's contributions

Outcomes

- Establishing a framework to solve the difficulties with passengers' strategic boarding/alighting behaviour in high frequency transit network
- Capturing the complexities of transit users' behaviour in a real transit system
- Capturing the fine details of spatio-temporal characteristics of a transit system
- Highlighting the importance of capturing transit users' preferences and their stochasticity in perception of transit network
- Rectifying the correlation among the stop choices (alternatives) and also the correlation among the transit mode choices.

Key findings

- The choice of access stop is affected not only by the attributes of impedance from the stop to the destination, but also, significantly, by the attributes of the stop itself, such as number of reasonable routes at the access stops and shelter availability.
- The results of the choice model revealed that transit users necessarily always did not choose the paths with the highest estimated utility or the highest estimated probability in the network. This observation can highlight the importance of capturing the subjectivities and indeterminacies which are known to exist in the perception of transit network among transit users.
- The results of correction factor coefficients (CFCs) confirm that treating for correlation among the stop choices can improve the modelling accuracy.

- The outcomes of the choice model indicated that applying the nesting structure can treat the dependencies among the stop choices at the mode level and consequently it can improve the model fit and the modelling calibration results.

Limitations

- The transit access choice model for measuring the network accessibility is not directly sensitive to the fare. Due to the zone-based structure of transit fares in SEQ, all access alternatives in the choice set of the model share the identical fares for travelling between the OD pair. As a result, travellers' sensitivities to fares could not be captured by the choice model directly.

Chapter 4: Accessibility Estimation and Validation for the Case Study

4.1 INTRODUCTION

As noted in Chapter 3, the developed logit discrete choice model can capture the access behaviours of travellers as well as the transit network characteristics. Reviewing the literature has also revealed another drawback to transit accessibility models: they are almost unaware of travellers' perception about the diverse available options in the transit network. The existing transit accessibility models have neglected the effect of multiple path options by utilising a single shortest path approach to estimate the accessibility between given O-D pairs.

In order to capture travellers' perception about the diverse available paths in the transit network, the proposed accessibility measurement needs to incorporate the universal set of available access options between given OD pairs. For this purpose, a composite network utility for the set of available access options needs to be developed and calculated. This proposed framework, in the context of a utility-based approach, will allow us to capture not only the benefits of the diversity of paths that the transit network can offer to the community but also, the users' stochasticity and subjectivity in perceptions of the transit network. It is important to note that contrary to the existing research that consider the stochasticity of the transit services (Hickman, 2001; Hickman & Bernstein, 1997), this research has assumed that the transit service is deterministic and that the model focuses on users' subjectivity in perception of transit network.

To highlight the potential advantages of the proposed measurement, the output of the accessibility model will first be visualised for the greater Brisbane area, and the results then compared with outputs of deterministic approaches such as shortest travel time to destination or shortest travel time to transit corridors. For this purpose, all of the "mesh blocks" in the greater Brisbane area are considered as origins in this research. Mesh block is the smallest geographical area defined by the Australian Bureau of Statistics (ABS, 2015b). The transit accessibility will be estimated for access to Brisbane CBD and to Gold Coast CBD as indicators of accessibility to work and leisure activities.

To emphasize the proposed model benefits compared to the traditional accessibility models, this chapter needs to answer the inquiries listed below:

- How diversity of transit services (both in-nest and cross-nest) can improve the transit accessibility?
- Can accessibility measurement based on the fastest travel time capture travellers' perception about the transit services?
- How can the cost of the travel affect the users' perception about the transit accessibility?
- Do train and no-train nests have a similar effect on the accessibility of transit network?

Chapter Outline

In this chapter, the first section explains the development of a random utility-based measurement for the proposed transit accessibility model (4.2). The proposed model is then tested and visualised for the case study (Greater Brisbane) regarding accessibility to the Brisbane CBD (4.3.1) and accessibility to the Gold Coast CBD (4.3.2). The effects of travel costs on accessibility will also be discussed in these sections. The results of comparing the proposed accessibility model with simple travel time accessibility models will be also demonstrated in these sections. The estimated logsum values will then be validated by the residential land prices (4.4). The chapter concludes (4.5) with a summary of the benefits of the proposed transit network accessibility model.

4.2 PROPOSED RANDOM UTILITY-BASED MEASURE

Utility-based approaches are popular for their potential in capturing the random nature of users' preferences and for their advantage of incorporating multiple attributes and multiple choices in modelling user perceptions of the available choice set. Although this approach has been used in a number of models, usually the accessibility models such as LUPTAI (Davidson, 2008), the random utility has been applied only to the choice of opportunities in destinations (benefit side); the network accessibility (impedance side), which can describe the performance of the transit network, is estimated simplistically, using simple distance or travel time variables.

The proposed utility-based estimation in this research is developed using the utility attributes from the access stop choice model estimated in Chapter 3. A random utility-based structure describing transit utility as a function of a diverse set of travel attributes estimated for a diverse set of stop choices and mode options in the transit system can capture, not only the importance of each attribute (e.g. travel time, number of transfers) in the users' perception, but also the stochasticity in perception of the transit network among travellers.

The developed algorithm to generate the universal set of reasonable access stop choices is presented in Section 3.4. Since a similar algorithm is applied to generate the choice set for the access choice model estimation, inclusion of the global set of reasonable access stop choices for accessibility estimation by this algorithm can be acceptable for the stochastic error term that is known to exist in the estimated utility function of the access stop choice model.

Given the access choice behaviour of travellers, structured as a nested logit model, the composite utility for network accessibility estimation should be calculated based on nested logsum calculations.

As shown in equations (4-1), the composite network utility (network accessibility), I_{od}^{τ}, to travel from o to d at time τ, can be described (Koppelman & Bhat, 2006) as:

$$I_{od}^{\tau} = \ln\left[\exp\left(\frac{\omega_{T}^{od,\tau}}{\mu_T}\right) + \exp\left(\frac{\omega_{NT}^{od,\tau}}{\mu_{NT}}\right)\right] \qquad (4\text{-}1)$$

Where $\omega_{T}^{od,\tau}$ and $\omega_{NT}^{od,\tau}$ are the logsums values for the "train" nest and the "no-train" nest respectively. These logsums estimations can be written as:

$$\omega_{T}^{od,\tau} = \ln \sum_{i \in C_T} \exp(\mu_T \times V_i) \qquad (4\text{-}2)$$

$$\omega_{NT}^{od,\tau} = \ln \sum_{i \in C_{NT}} \exp(\mu_{NT} \times V_i) \qquad (4\text{-}3)$$

with the following symbolisation:

μ_T : Nest parameter for nest "train" ($1 < \mu_T = 4.12$)

μ_{NT} : Nest parameter for nest "no-train" ($1 < \mu_{NT} = 4.10$)

C_T : Set of all alternatives in nest "train",

C_{NT} : Set of all alternatives in nest "no-train",

V_i : Systematic utility of choice i (calculated based on parameters in Table 3-5).

The composite logsum network accessibility, I_{od}^{τ}, is calculated from two terms, $\omega_T^{od,\tau}$ (logsum of all available train stations in the choice set) and $\omega_{NT}^{od,\tau}$ (logsum of all available bus stops and ferry terminals in the choice set), presents the expected maximum utility of the access choices that are available to transit users when they travel to their destinations by transit services.

The nest parameters μ_T and μ_{NT}, calculated in the access choice model (Chapter 3), indicate significant correlation among the utility error terms of the alternatives in each nest. This correlation, reflected in the calculation of I_{od}^{τ}, declines the diversity benefits inside the defined nests ("train" and "no-train"). Consequently, the benefit of having two choices in the same nest is less than the benefit of having these choices in two different nests. For instance, as a result of this nesting structure, we should expect higher accessibility benefits when a transit user has access to two different nest choices (bus and train) in comparison with a situation when he/she has access either to two bus choices or to two train lanes. This effect should be observed in the case study results in the next section, where better values of I_{od}^{τ} are observed in the locations that have access to all transit modes.

Since the proposed composite network measurement, I_{od}^{τ}, is defined as the logsum of the utility of service, the higher amounts of I_{od}^{τ} indicate a better level of service and consequently a better level of accessibility.

4.3 SEQ CASE STUDY ANALYSIS

The greater Brisbane area was chosen for testing the proposed accessibility measure in this research. For this purpose, accessibility is measured for all greater Brisbane area for accessing to Brisbane CBD and to Gold coast CBD as indicators of accessibility to work and leisure activities.

The accessibility values are calculated for journeys in the morning peak (7am) and with the assumption of a single opportunity located in the Brisbane and Gold coast CBDs. Calculations are also performed at the spatial resolution of a mesh block. Accordingly, the accessibility calculation should be performed for a total of 24,465 mesh blocks in the case study.

4.3.1 Logsum network accessibility to Brisbane CBD

For measuring the impedance of accessibility to Brisbane CBD, three logsum measures, $\omega_T^{od,\tau}$, $\omega_{NT}^{od,\tau}$ and I_{od}^{τ}, are calculated for all suburbs (24,465 mesh blocks) in the greater Brisbane area, SEQ. These logsum measures are calculated for transit journeys in the morning peak (7am) of a weekday service, and with the destination located in the Brisbane CBD.

Representing the logsum measures for $\omega_T^{od,\tau}$, $\omega_{NT}^{od,\tau}$ and when both nests are available ("train" and "no-train"), versus fastest travel time revealed an interesting observation about the effect of transit diversity benefit on the accessibility. Figure 4-1, 4-2 and 4-3 show respectively the scatter plots of the calculated logsum measures for $\omega_T^{od,\tau}$ (only train nest), for $\omega_{NT}^{od,\tau}$ (only no-train nest) and for a situation when both nests are available versus the fastest travel time (T_{od}^{τ}) for all the mesh blocks in the case study.

T_{od}^{τ}, represents the fastest travel time to destination (Brisbane CBD) from the given origin at the departure time τ.

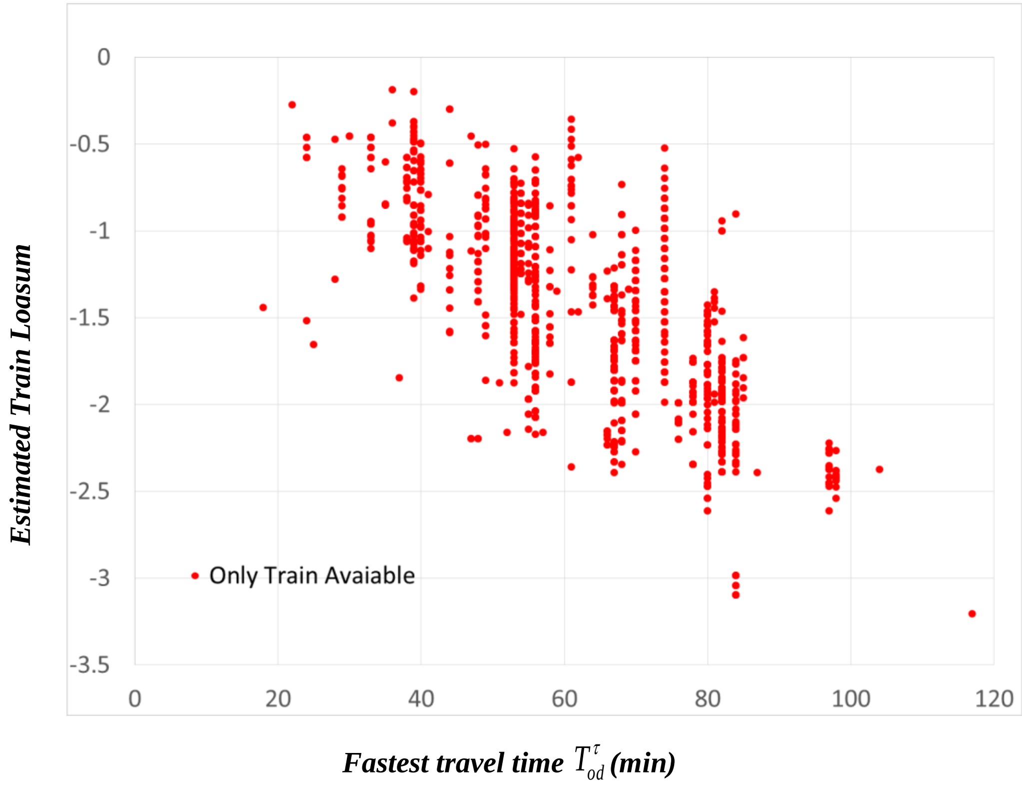


Figure 4-1: Train logsum ($\omega_T^{od,\tau}$) vs. fastest travel time (T_{od}^{τ}) for accessibility to Brisbane CBD (only train available)

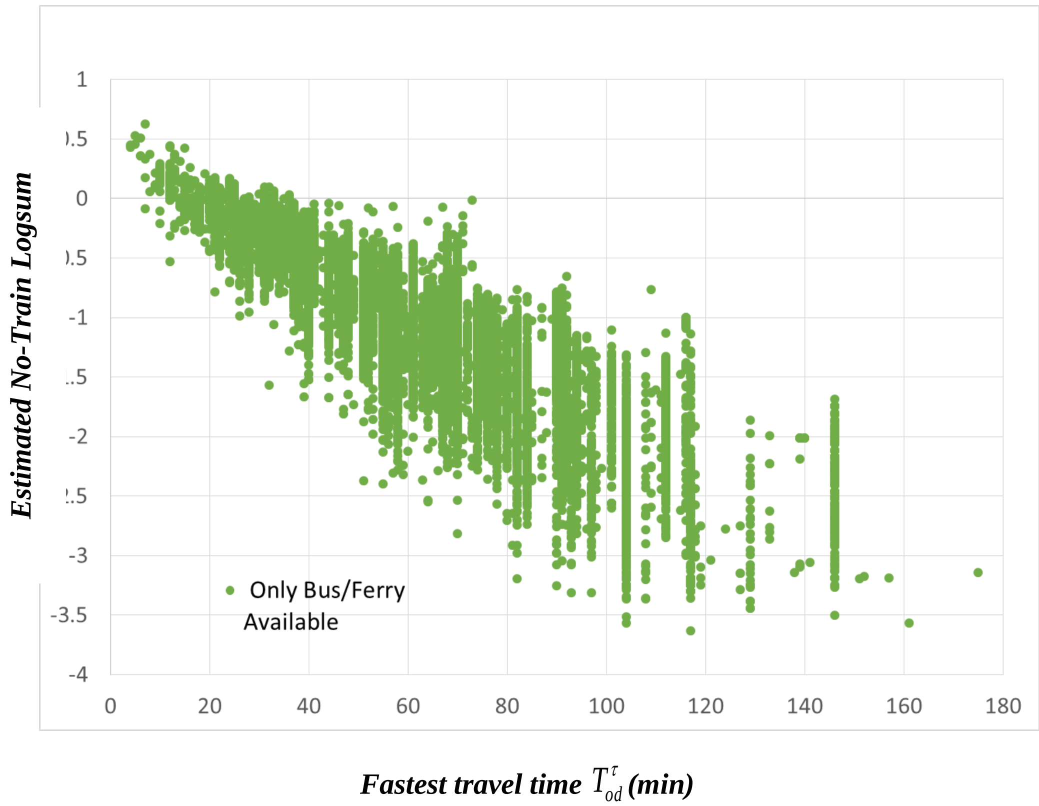


Figure 4-2: No-train logsum ($\omega_{NT}^{od,\tau}$) vs. fastest travel time (T_{od}^{τ}) for accessibility to Brisbane CBD (only bus/ferry available)

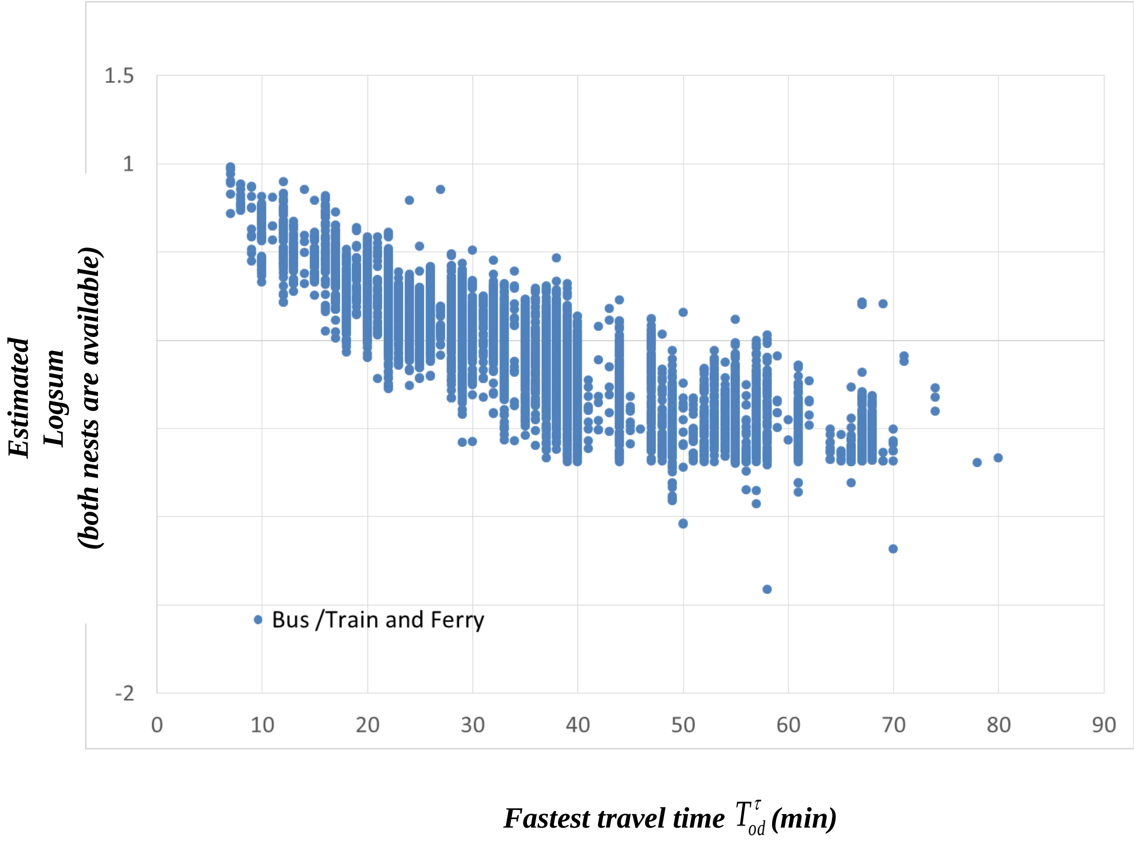


Figure 4-3: Estimated logsum (I_{od}^{τ}) (both nests are available) vs. fastest travel time T_{od}^{τ} for accessibility to Brisbane CBD

It can be observed from the scatter plots for train only (Figure 4-1) and bus/ferry only (Figure 4-2) that the maximum of the train logsum is lower than this value for no-train facilities. Possible reasons can be imagined for this are longer walking distances for accessing train stations, and higher numbers of services available for travelling with bus/ferry in the transit network. Bus/ferry transit stops are generally distributed geographically better than train stops, which reduce the average access walking to reach bus/ferry stops, in comparison with reaching train stations. However, the logsum outputs for train only journeys shows a higher minimum logsum (-3.2), in comparison with the bus/ferry logsum (-3.63). A possible reason for this observation is that the train services generally provide faster journeys for their catchment areas due to higher train travelling speeds. Consequently, the decline in the estimated train logsum due to an increase in distance from CBD is relatively smaller than these values estimated for bus/ferry logsum. This statement can be a correct expression as a research that carried out in SEQ in 2012 by DTMR (Department of Transport and Main Roads) indicates for faster O-D train trips (23 km/h) in comparison with O-D bus (14 km/h) and ferry (15 km/h) trips in the transit network (DTMR, 2012).

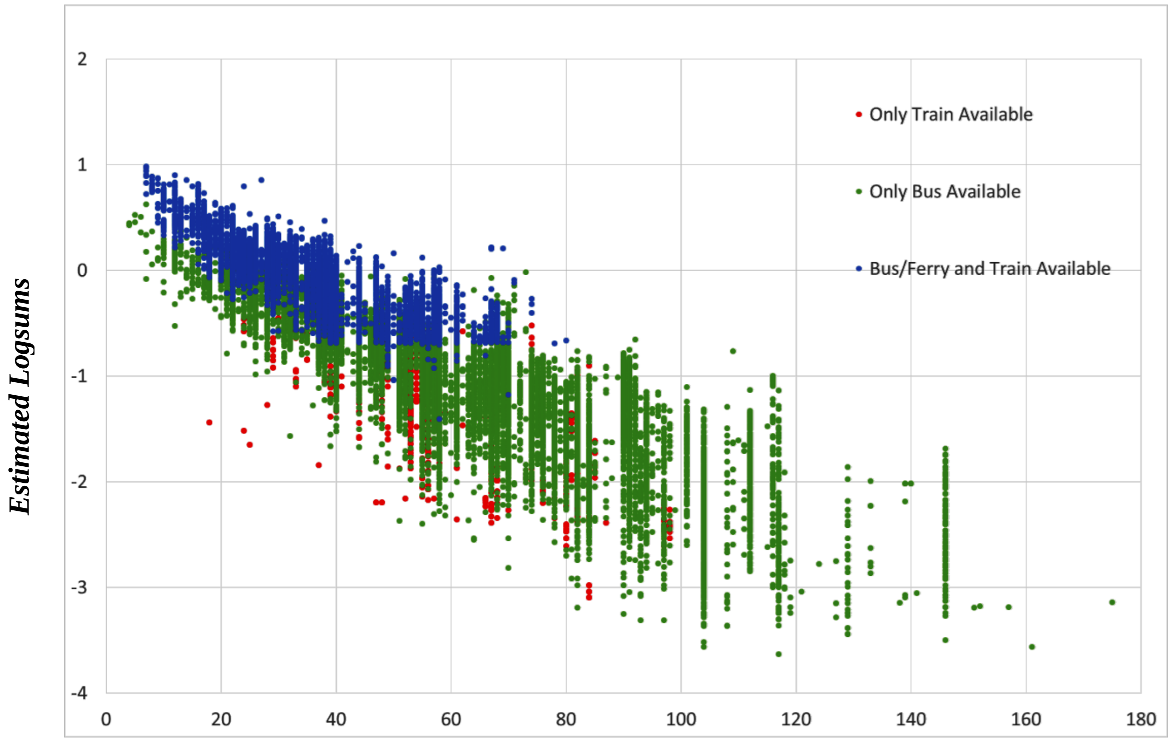
These scatter plots (Figures 4-1 to 4-3) also show a general decline in logsum with the increase in travel time. This observation intuitively confirms the general sensitivity of logsum values to the travel time or distance to the CBD.

For better judgment about the logsum outputs, all logsum values (train only, bus/ferry only, and train/bus/ferry) are merged in one graph (Figure 4-4). An important observation that should be highlighted from Figure 4-4 is the vertical pattern of data points in the scatter plot. This pattern shows that there are many locations in the case study that have equal travel times to the CBD, but that the estimated logsum (network utility) from these locations can vary across a wide range (changing up to three units in some cases). In another word, these locations may be served by different levels of transit services but with similar travel time to CBD.

These outcomes can confirm the capability of the model to capture the fine details of the spatial-temporal transit characteristics in a real network, which cannot be observed by simple travel time estimations.

Reviewing the graph for the situation that all transit services are available (Figure 4-3), also revealed another important observation: the areas served by both nests (train and bus/ferry) for travelling to the CBD show significantly better logsum results than those in other areas in the case study served by either train services (Figure 4-1) or bus/ferry services (Figure 4-2) alone.

This observation highlights the capability of the model, in a practical case study application, of capturing the benefit that the diversity of modes can offer to the community.



Fastest travel time T_{od}^{τ} ***(min)***

Figure 4-4: All estimated logsums vs. fastest travel time T_{od}^{τ} **for accessibility to Brisbane CBD**

Visualising the Logsum accessibility to Brisbane CBD

To provide better understanding and judgment about the outputs of the proposed network accessibility model for transit, the calculated logsum accessibility to Brisbane CBD is visualized by ArcGIS (Sandhu & Chandrasekhar, 2006) for the model's nests individually along with total calculated logsum. Figure 4-5 presents the estimated logsum of the nest "train", $\omega_T^{od,\tau}$, from all Brisbane suburbs to Brisbane CBD. This map demonstrates the service that only the rail network provides to the CBD. In the same fashion, Figures 4-6 and 4-7 present the logsums for "no-train", $\omega_{NT}^{od,\tau}$, and the combined logsum , I_{od}^{τ}. The logsum of the nest "no-train" demonstrates the service that only the bus and ferry network provide to the CBD. This graph basically depicts the hypothetical situation when there is a temporary failure in the entire train network (e.g. during a storm).

In the same manner, the total logsum accessibility, I_{od}^{τ}, associates with the service that the whole transit services, with the three modes of train, bus and ferry, can provide for accessing to the CBD.

Several interesting observations can be made from these generated maps. First, the high level of logsum observed in Figure 4-7, compared to those of Figure 4-5 (only train logsum) and Figure 4-6 (only bus and ferry logsum), is associated with the diversity of modes available to travel to the CBD during the morning peak. It reflects the transit users perceive the diversity of available options as a positive utility. Capturing these diversity benefits is one of the main advantages and contributions of the proposed model.

Second, the general logsum value resulting from bus/ferry services for travelling to the CBD appears to be higher than this value for only train services. This observation could also relate to higher number of available routes for the bus/ferry nest (particularly for areas around the CBD), higher numbers of access options (bus/ferry stops) and possibly lower walking distances for access to bus/ferry stops in comparison with the train services. However, the effectiveness of the train mode becomes more highlighted when all the services across the modes are combined (see Figure 4-7) and as a result, this increases the level of accessibility by transit services.

The third interesting observation is related to the average sensitivity of the logsum results to distance from the CBD. This sensitivity is highly observed in bus/ferry services (Figure 4-6) and in the total logsum (Figure 4-7) as compared to train services (Figure 4-5). This observation aligns with our initial statement from the scatter graphs for only train and only bus/ferry services logsum which indicates for possible higher density of bus network in the suburbs closer to the CBD and/or higher speed of train in comparison with bus/ferry services.

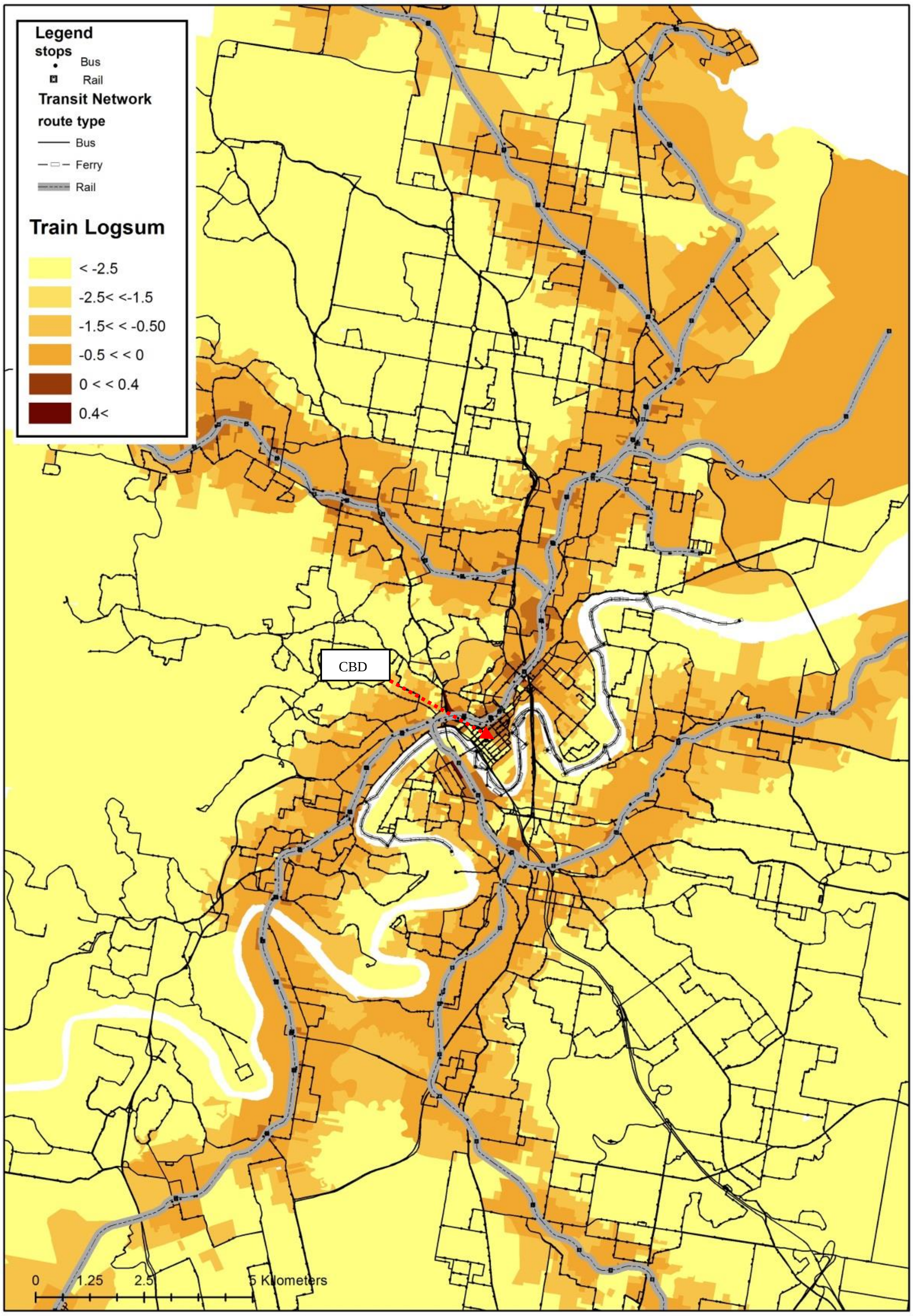


Figure 4-5: Estimated Train logsum ($\omega_T^{od,\tau}$) to access Brisbane CBD (departing at 7:00 am)

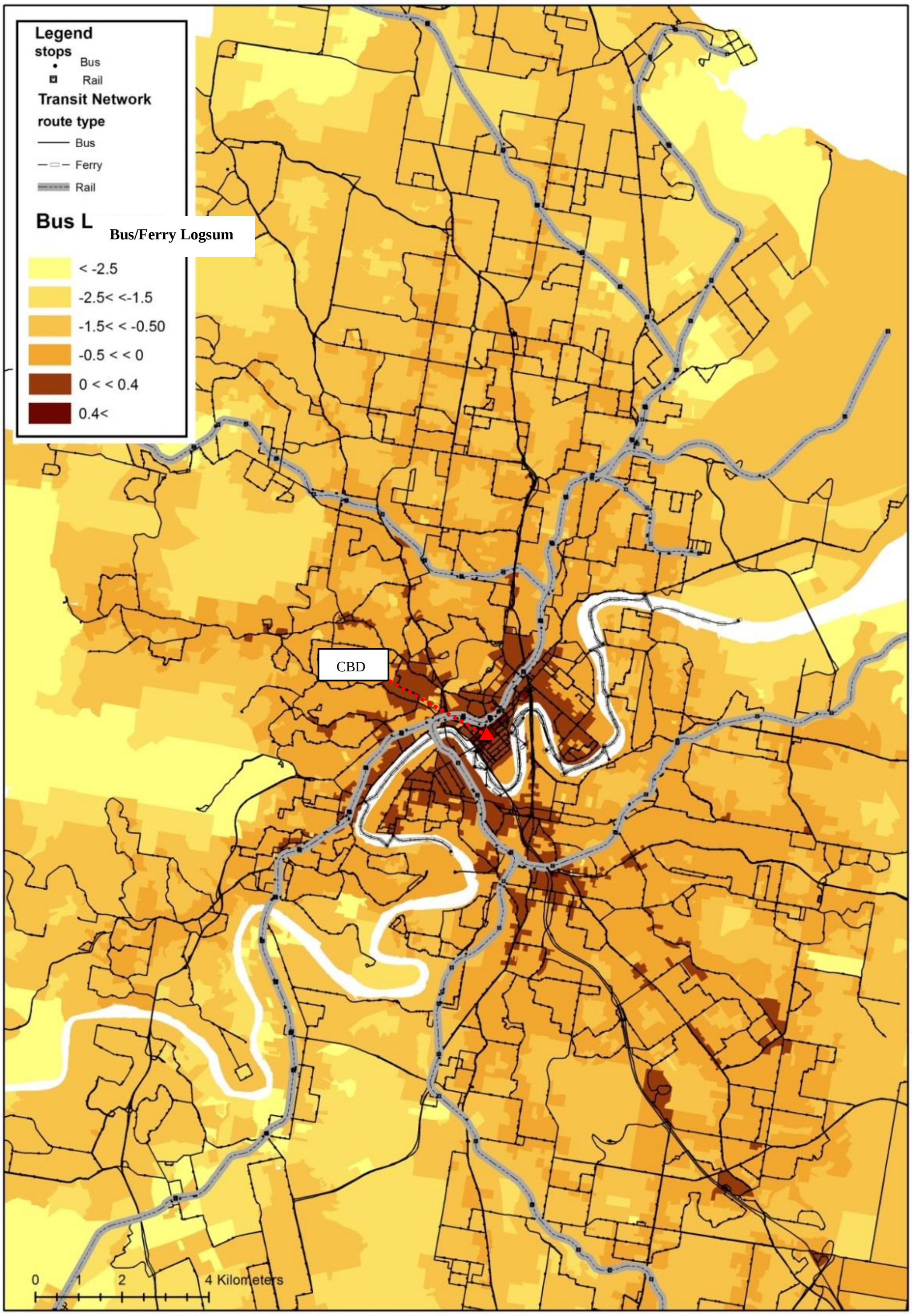


Figure 4-6: Estimated No-train logsum ($\omega_{NT}^{od,\tau}$) to access Brisbane CBD (departing at 7:00 am)

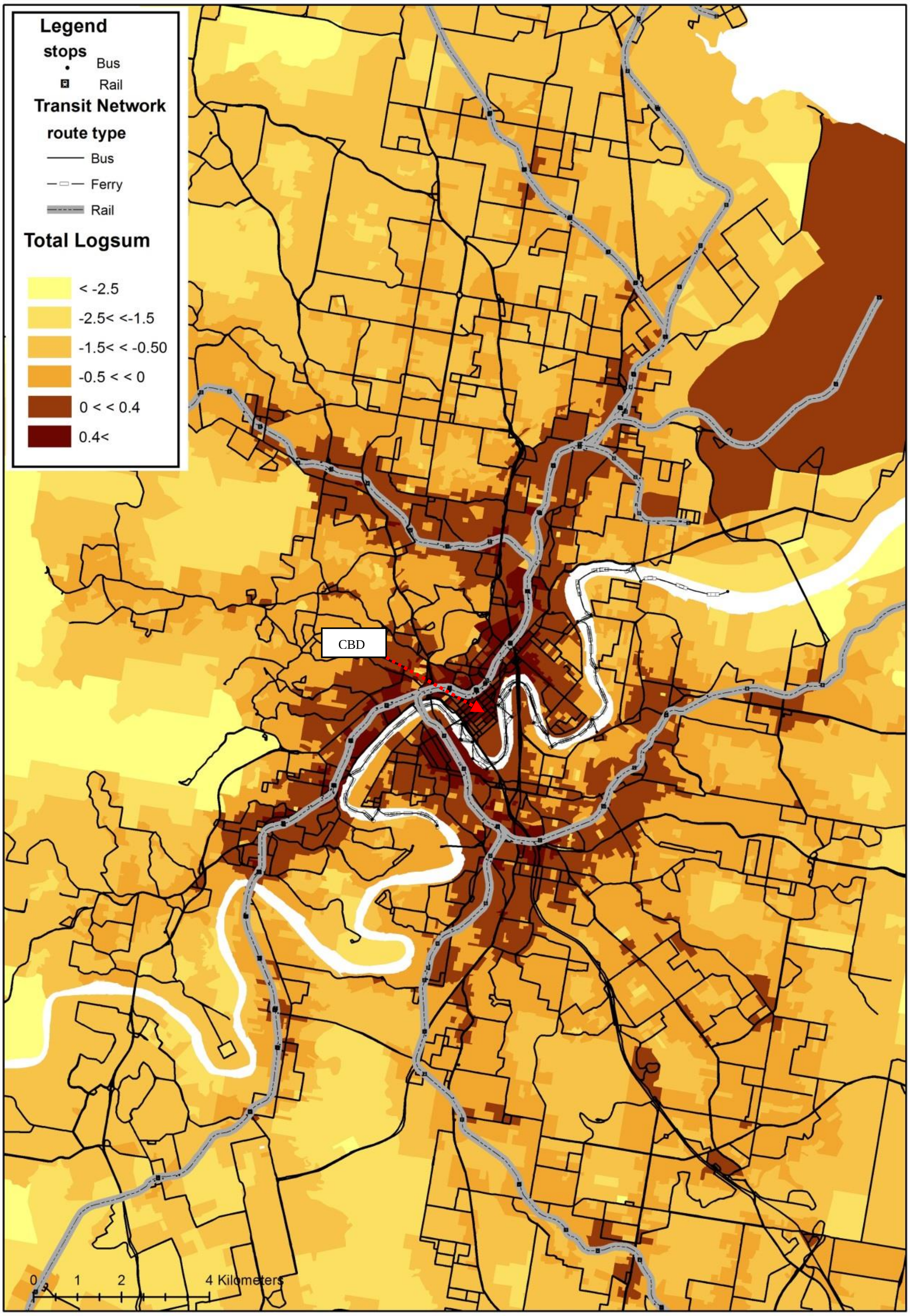


Figure 4-7: Estimated combined logsum (I_{od}^{τ}) to access Brisbane CBD (departing at 7:00 am)

Incorporating the Fare into the Logsum Accessibility

One theoretical limitation of this model as a transit network accessibility measurement for the transit services is that the model is not directly sensitive to the fare: this is an important disutility in the transit accessibility. As noted in the Chapter 3, due to the zone based structure of transit fares in SEQ, the developed access stop choice model could not capture the sensitivity of transit users to the fare. Because of the zone based fare structure, all access alternatives in the choice set of the model share the same identical fares for travelling between the OD pair. As a result, travellers' sensitivities to fare could not be captured in the choice model.

In order to incorporate the transit fares, we develop another logsum measure, A_{od}^{τ}, an adjusted definition of I_{od}^{τ}. This adjusted logsum proposes a method to add the fare effects as a penalty to the travel impedance. This adjusted logsum measure can be defined as follows:

$$A_{od}^{\tau} = I_{od}^{\tau} + \left(\frac{-0.00822}{VOT} \times F_{od}^{\tau}\right) \qquad (4\text{-}4)$$

where:

F_{od}^{τ} is the transit fare for travelling from o to d at time τ,

VOT is Value of Time in Australia

The term $\frac{-0.00822}{VOT}$ is an estimate of the utility coefficient of fare expenses. This coefficient is estimated by dividing the coefficient of time in the access stop choice model (FastestTT, which is -0.0082 per minute) by the value of time (VOT) in Australia, which is considered to be 13AUD/hr (Douglas & Wallis, 2013).

This adjusted logsum, A_{od}^{τ}, is calculated for travelling to the Brisbane CBD at 7 am weekday service from all mesh blocks in Brisbane. The ticket fares, F_{od}^{τ}, for 2009 in SEQ were provided from Translink based on single ticket fares. Figure 4-8 presents the adjusted and original logsum versus the fastest travel time; Figure 4-9 presents these adjusted values for logsum accessibility to Brisbane CBD. As expected, and as can be easily observed in Figures 4-8 and 4-9, A_{od}^{τ} is slightly smaller than the original total logsum, I_{od}^{τ}. The difference between the two measures A_{od}^{τ} and I_{od}^{τ}, is more pronounced in the suburbs that are located far from the CBD and consequently that have higher transit fares for travelling to the CBD (fares range from 2.40 AUD to 18.80 AUD).

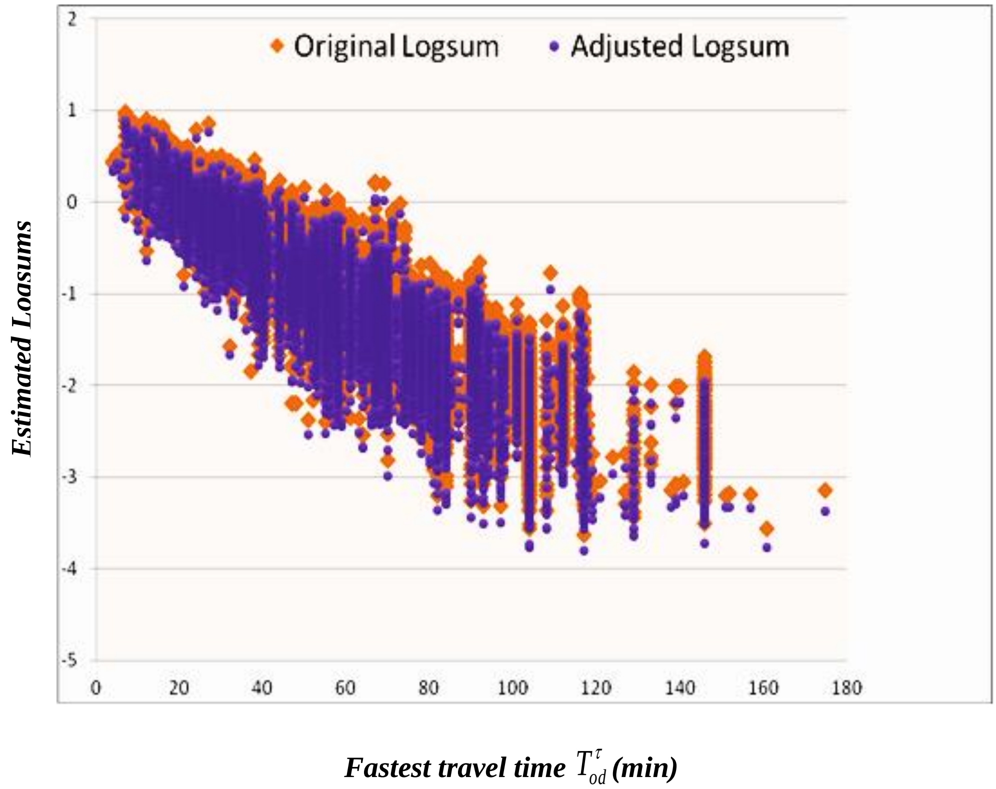


Figure 4-8: Adjusted and original logsums vs. fastest travel time T_{od}^{τ} for accessibility to Brisbane CBD

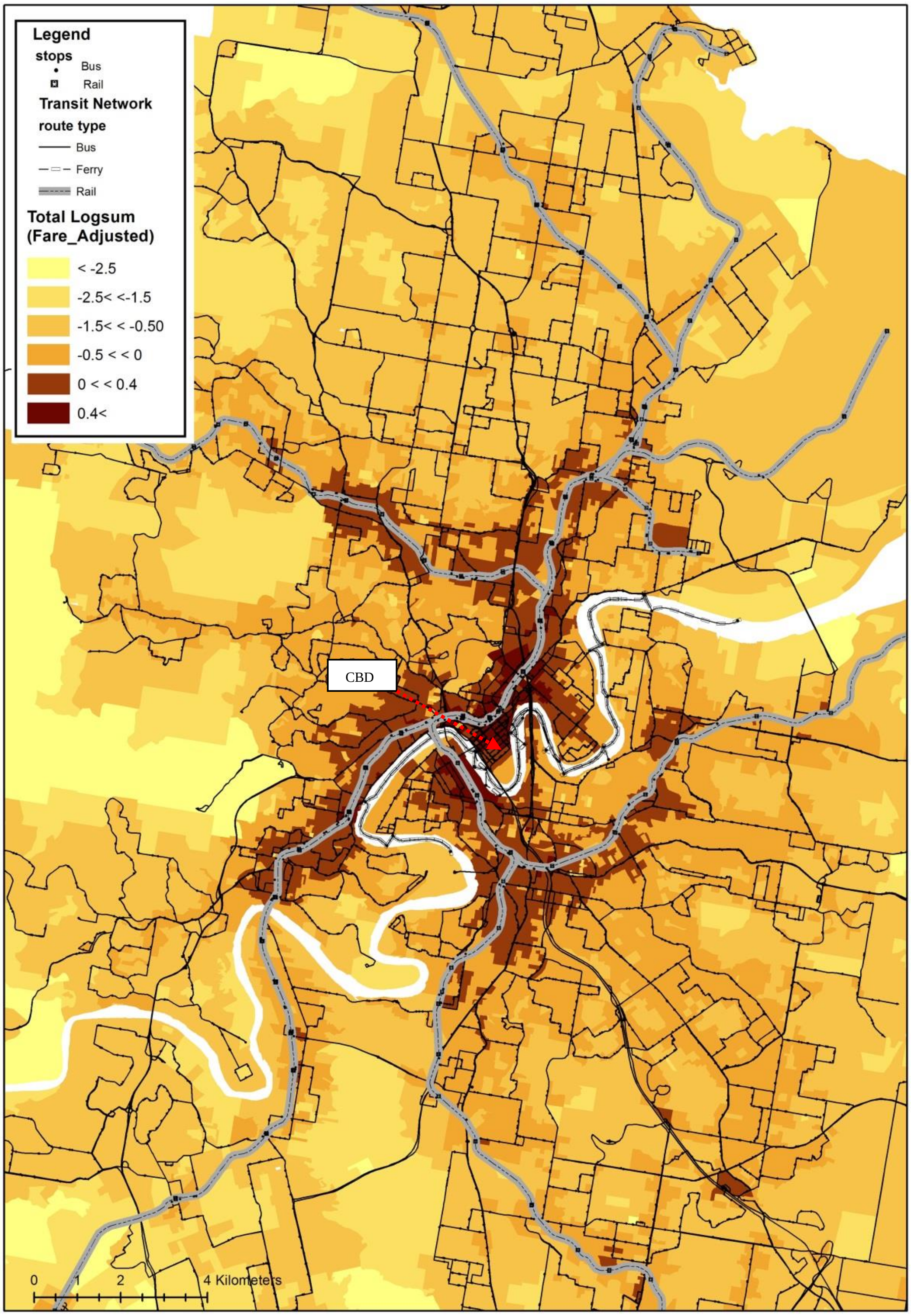


Figure 4-9: Adjusted logsum (A_{od}^{τ}) to access Brisbane CBD

(departing at 7:00 am)

Examining the network accessibility results by only-travel-time approaches

To provide better understanding about the advantage of the proposed transit network accessibility estimation compared with the existing only-travel-time measurements, the calculated logsum for accessibility to Brisbane CBD needs to be compared with these traditional impedance measurements. This research used the fastest travel time to transit corridors, TC_{od}^{τ} , and the fastest travel time to CBD, T_{od}^{τ}, as the baselines for evaluating the effectiveness of the proposed composite measurement.

The fastest travel time to transit stops and Brisbane CBD are calculated by the trip-based shortest path (TBSP) algorithm for all greater Brisbane mesh blocks and the results are visualized in Figures 4-10 to 4-13. Since the accessibility measure is dimensionless, comparing the two different measuring techniques is not easy. In order to compare the fastest travel time with logsum values, all colour coded values for the travel time graphs and the adjusted logsum graph are sorted with the same order increment. This means that the interval ratio between colour coded values for the travel time graphs and the adjusted logsum graphs are in the same order.

Examining the proposed network accessibility model by a "System Accessibility" approach

As explained in Chapter 2, one of the popular accessibility measures in the context of transit accessibility is "System Accessibility" or accessibility to stops which applied in a number of transit accessibility research such as Lei and Church (2010), Foda and Osman (2010), Azar, et al. (1994) and El-Geneidy, et al. (2010). Figure 4-10 presents the results of a system accessibility measurement (fastest travel time to stops) and logsum model for a Brisbane suburb (Sunnybank). It is important to note that the system accessibility measurement demonstrates only for stops with available paths to Brisbane CBD: if a stop is not served by any reasonable path to the CBD, it is not considered in this estimation.

Comparing the results of the "System Accessibility" model with the proposed logsum model highlights that these approaches are not capable to capture the travellers' perception in the transit system. These approaches only focus on "first-mile" problem only and do not provide an overview about the accessibility in the entire of transit system. As shown in Figure 4-10, system accessibility approach identified several mesh blocks with reasonable walking time to transit stops and consequently with high "System Accessibility" value. However, these mesh blocks generally do not have appropriate access to CBD due to long travel time or other disutility of transit service. This observation confirms the fact that access to transit stops cannot be a proper measurement to evaluate the impedance of accessibility as it is completely blind to travellers' difficulties in their whole journeys in the transit system and generally it overestimates the users' accessibility.

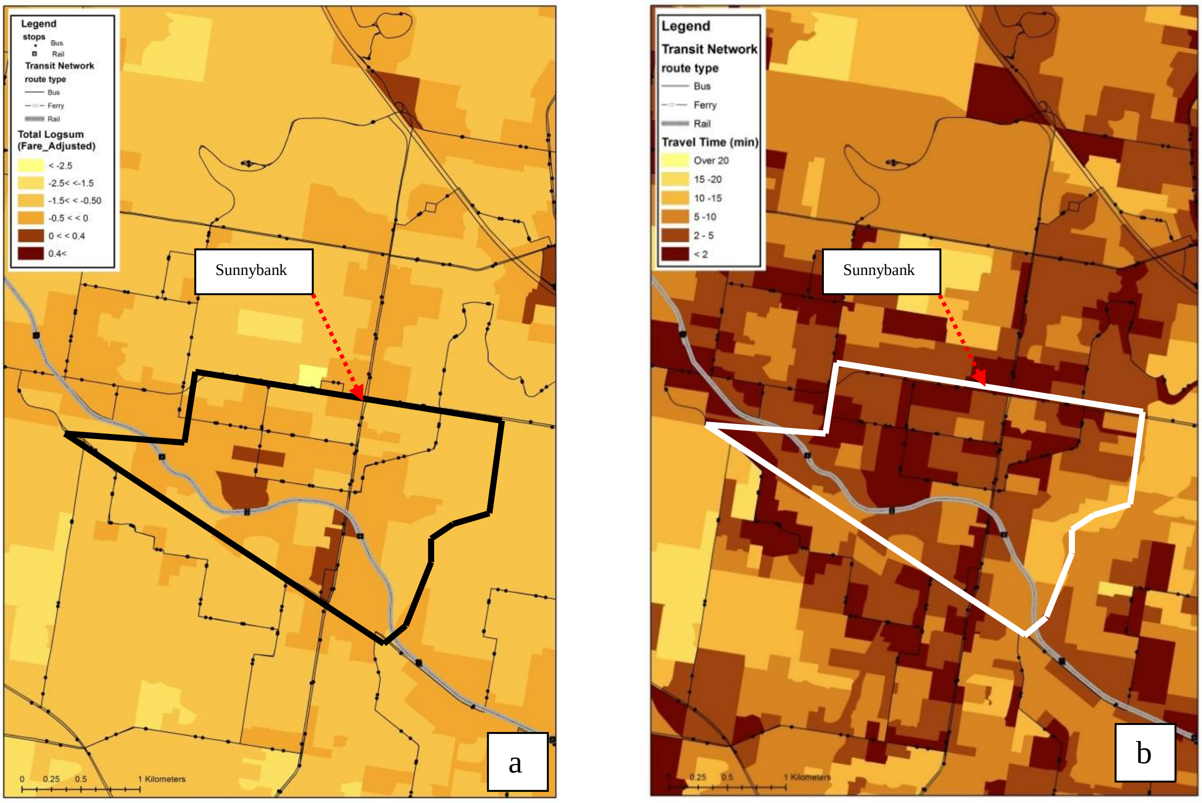


Figure 4-10: Estimated logsum measure (a) vs. Fastest travel time (TC_{od}^{τ}) to transit corridor (b) for accessibility to Brisbane CBD from Sunnybank area (departing at 7:00 am)

Examining the proposed transit network accessibility model by an only-travel-time accessibility approach (accessibility to Brisbane CBD)

Another baseline for logsum model evaluation which is used in this research is the fastest travel time to destination (Brisbane CBD). Fastest or average travel time to destination is a popular impedance factor that has been used in a number of the accessibility models to measure the transit network accessibility.

To have a better overview about the logsum values, Table 4-1 provides an example based on the logsum values in Figure 4-11. The fastest travel time values in this table are identical to fastest travel time cut-off values in the legend of Figure 4-11. Table 4-1 also can highlight difficulties in interpreting logsum values in an accessibility measurement. These examples are based on the assumption that the routes passing the stops do not have any overlaps with each other and that travel users have only two available stop options (bus and/or train).

Table 4-1: Examples for logsum values

Logsum Value	Available modes	AccessWalk (min)	FastestTT (min)	MinTransfer	NumRoutes	Shelter Availability
0.4	Train	3	15	0	2	Yes
	Bus	6	15	0	4	No
0	Train	4	25	1	2	Yes
	Bus	10	25	0	6	Yes
-0.5	Train	15	35	0	1	No
	Bus	13	35	1	5	No
-1.5	Train	32	55	1	2	Yes
	Bus	25	55	1	5	Yes
-2.5	Train	25	75	2	1	Yes
	Bus	N/A	N/A	N/A	N/A	N/A

One important observation should be made from figure 4-11 is although the fastest travel time provides an overview about the impedance of transit services, it cannot capture the passengers' perceptions about the disutility of distance to transit services (access walk); also, it is not sensitive to other transit service characteristics (e.g. transit mode diversity, number of available routes and number of transfers). Many mesh blocks around the CBD are identified by similar travel time to the CBD although they are located with various distances to the transit network and are served by different levels of transit services. Examples of these cases will be shown in detail in Figure 4-12 and Figure 4-13.

Figure 4-12 shows an enlarged map for the adjusted logsum, A^{τ}_{od}, for the suburbs around the CBD. The mesh blocks with highlighted borders in green colour all have a 22-minute fastest travel times to the CBD; however, the adjusted logsum, A^{τ}_{od}, calculated for these mesh blocks, ranges from about -0.67 to about +0.52. Among these, the mesh blocks with relatively smaller logsum values of A^{τ}_{od} (mostly between -1.5 and -0.5) are located on the bank of the Brisbane River (marked by "A" or red oval) and also, at Kelvin Grove and Holland Park suburbs (marked by "B" or gray oval) where the access to the transit network is provided by bus stops only. However, the reasons behind the low level of logsum values in these areas are completely different. It is calculated that a main portion of the 22-minute travel time to the CBD, from the area which is marked “A”, is for the access walk to stops (about 5 to 10 minutes). These long access walk distances in these areas reduce the estimated logsum in average due to high disutility of access walk in perception of the SEQ transit users (from access choice model results). On the other hand, the residents of mesh blocks marked “B” should walk less to bus stops, but they have an inferior diversity of options to the CBD. As a result, general logsum values for the mesh blocks at Kelvin Grove and Holland Park are approximately equivalent to these at the bank of Brisbane River (marked by “A”).

In the other mesh blocks located close to train corridors (marked by “C” or blue oval), the situation is a little different. These mesh blocks, located mostly in Greenslopes, Indooroopilly and Highgate Hill suburbs, are served more effectively by multiple train and bus routes within a short walk to stops. People in “C” blocks have the option to choose between bus and train, although they probably have to walk a little further to reach any of the modes. The positive effect of having such an option can explain the difference between the estimated logsum of “A” and “B” mesh blocks ($-1.5 < A_{od}^{\tau} < -0.5$) on the one side and the logsum values of “C” mesh blocks ($-0.5 < A_{od}^{\tau} < 0$) on the other side, although the travel time for journeys departing at 7 am is equal to 22 minutes for all of these mesh blocks.

Another observation can be made from the mesh blocks located in Kangaroo Point suburb (marked by “D” or yellow oval). These area shows mixed logsum values between ($-1.5 < A_{od}^{\tau} < 0$) although the travel time to CBD for all these highlighted mesh blocks are 22 minutes, and they are served by multiple bus services to the CBD. The mesh blocks close to the bus stops show higher logsum values, compared with those mesh blocks further from stops. Again, this example shows the effect of walking distances and diversity of options in the perception of transit users; these cannot be captured by accessibility approaches based on simple travel time estimation.

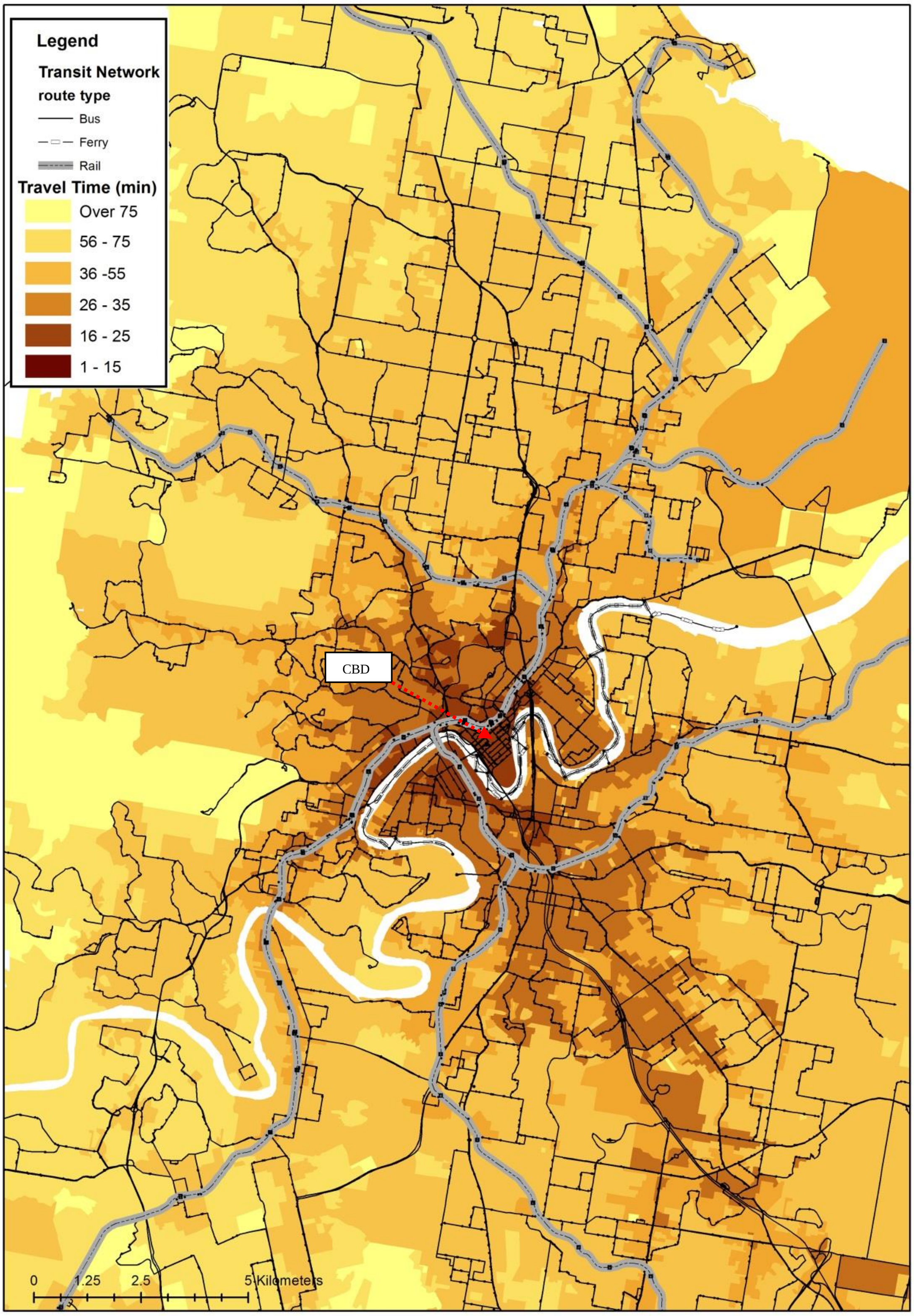


Figure 4-11: Fastest travel time (T_{od}^{τ}) to access Brisbane CBD (departing at 7:00 am)

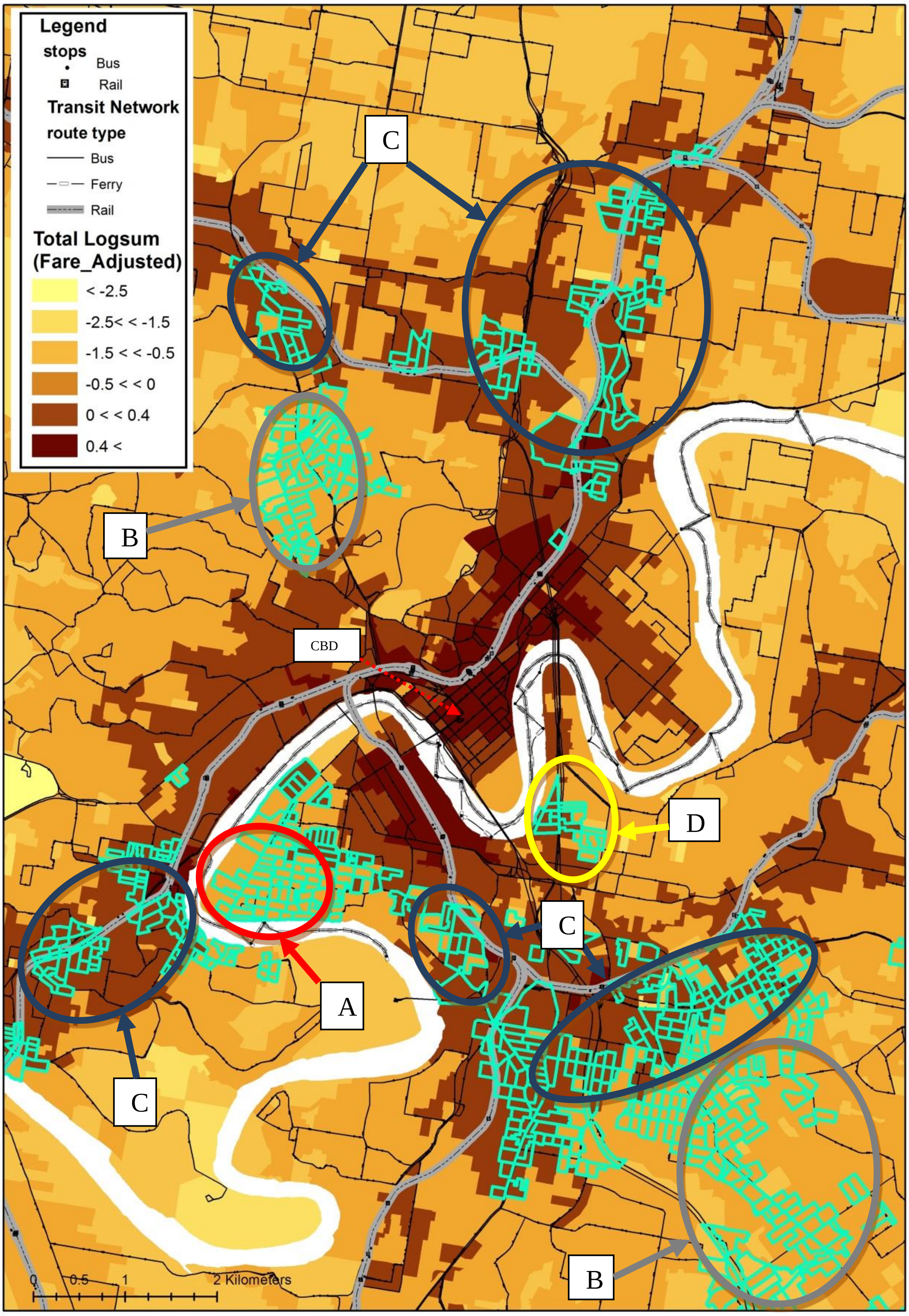


Figure 4-12: Logsum (A^{τ}_{od}) scaled-up map of the suburbs with 22 min travel time to CBD (departing at 7:00 am)

Another interesting outcome which demonstrates the sensitivity of the accessibility model to the transit service characteristics can be observed in Figure 4-13. In this figure, all the mesh blocks with 29-minute travel time to the CBD are highlighted in green colour; however, the adjusted logsum, A_{od}^{τ}, calculated for these mesh blocks ranges from about -1.5 to about +0.43.

The highlighted mesh blocks located in the suburbs of Chelmer and Graceville (marked by “F” or blue oval) show significantly lower logsum values than these of the highlighted mesh blocks at Indooroopilly and Taringa (marked by “E” or red oval).

As shown in Figure 4-13, both of these areas (“E” and “F”) are located within reasonable distance of the train corridor and have identical travel time to CBD (29 min); however, the highlighted mesh blocks at Indooroopilly and Taringa (“E”) show significantly higher logsum values in compare with the areas around the train lanes at Chelmer and Graceville suburbs (“F”).

A possible reason behind this observation is that the highlighted mesh blocks at Indooroopilly and Taringa (“E”) are served by express services to the CBD (for transit journeys in the morning peak of a weekday service), while the highlighted areas at Chelmer and Graceville do not benefit from these services at the morning peak time (7:00 am).

This example from the case study confirms the perception of transit users about the value of having a back-up plan in case of service disruption or a long delay on one route and highlights the advantage of the proposed measurement to capture travellers’ feeling about transit service characteristics (e.g. number of available routes).

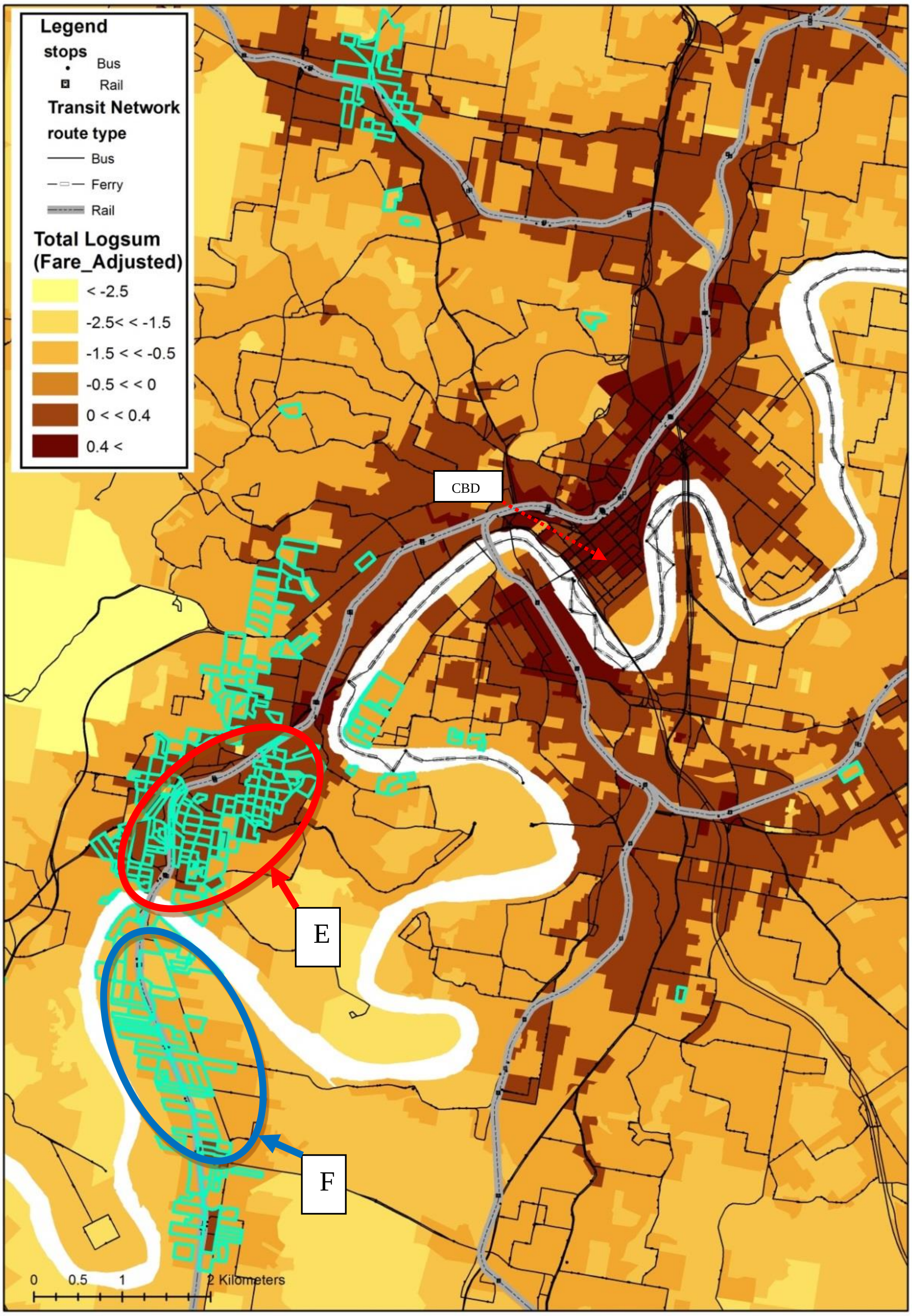


Figure 4-13: Logsum (A_{od}^{τ}) scaled-up map of the suburbs with 29 min travel time to CBD (departing at 7:00 am)

4.3.2 Accessibility to Gold Coast CBD

Gold Coast city is an important destination for Brisbane residents as it is a favourite tourism and leisure activities centre. The city, located approximately within 94 km from Brisbane city, attracts 12 million visitors each year, most of them from Brisbane suburbs. Due to existing sport and tourist facilities, the city also successfully hosts important events and festivals such as the 2018 Commonwealth Games, GC600 which possibly attracts more trips from Brisbane areas, according to Gold Coast City Council website (GCCC, 2015) . The Figure 4-14 provides an overview of Gold Coast CBD in relation to Brisbane.

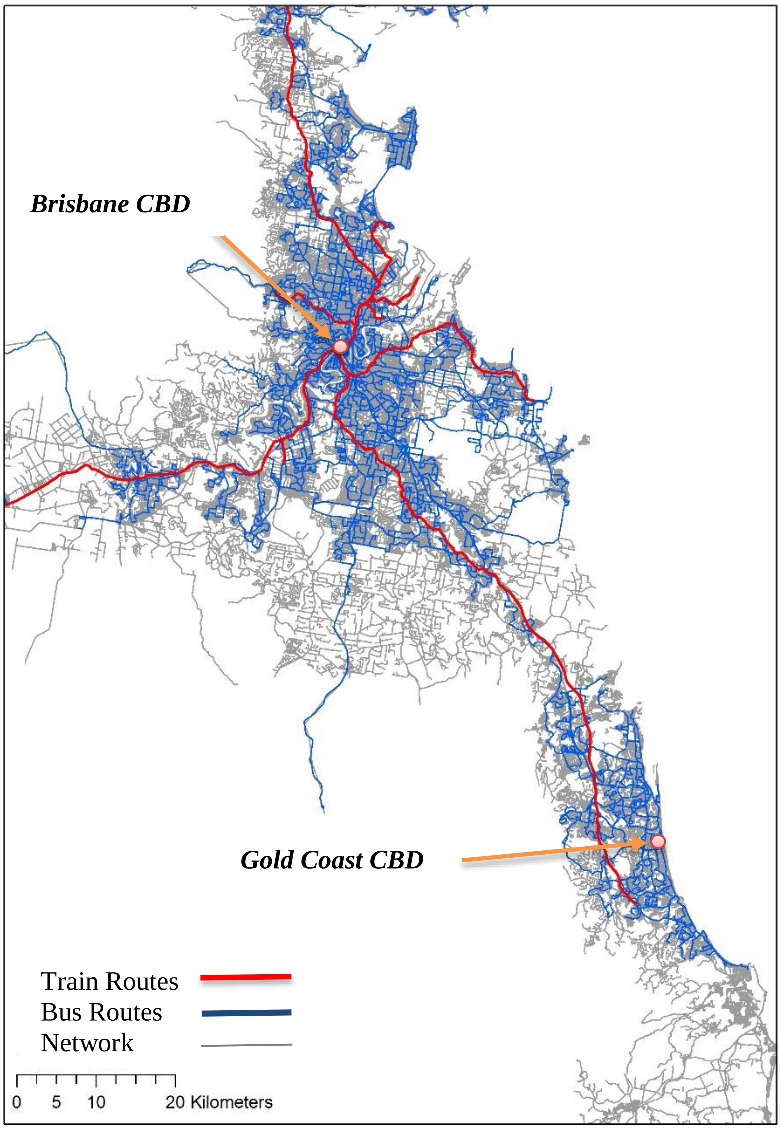


Figure 4-14: An overview of Gold Coast CBD in relation to Brisbane CBD

As explained in Chapter 3, estimating the choice model revealed that the perception of transit users to disutility of transfer is extremely high. On the other hand, due to the structure of public transport in Brisbane, generally all the suburbs in the greater Brisbane area are served by direct transit services (without transfer) to the CBD. As a result, calculating and visualizing the logsum values for access to the Brisbane CBD cannot highlight and capture travellers' perception about the disutility of transit transfer. Estimation of the transit accessibility to Gold Coast CBD not only provides an overview of the transit accessibility of the greater Brisbane areas to leisure activities, but also highlights the advantages of the proposed logsum model, which may not be obvious from accessibility to the Brisbane CBD. The results of the model for accessibility to the Gold Coast CBD are calculated and visualized in the following section.

Visualising the Logsum accessibility to the Gold Coast CBD

Similar to the graphs of accessibility to the Brisbane CBD, the logsum values for the nest "train" $\omega_T^{od,\tau}$ and the nest "no-train" $\omega_{NT}^{od,\tau}$ for all Brisbane suburbs, calculated for accessibility to the Gold Coast CBD, are presented in Figure 4-15 and Figure 4-16 respectively. Figure 4-15 shows the service provided by only the rail network for Brisbane residents to access to Gold Coast CBD; Figures 4-16 demonstrates the service that only the bus and ferry networks provide for accessing the Gold Coast CBD. Figure 4-17, also presents combined logsum (I_{od}^{τ}) to access the Gold Coast CBD.

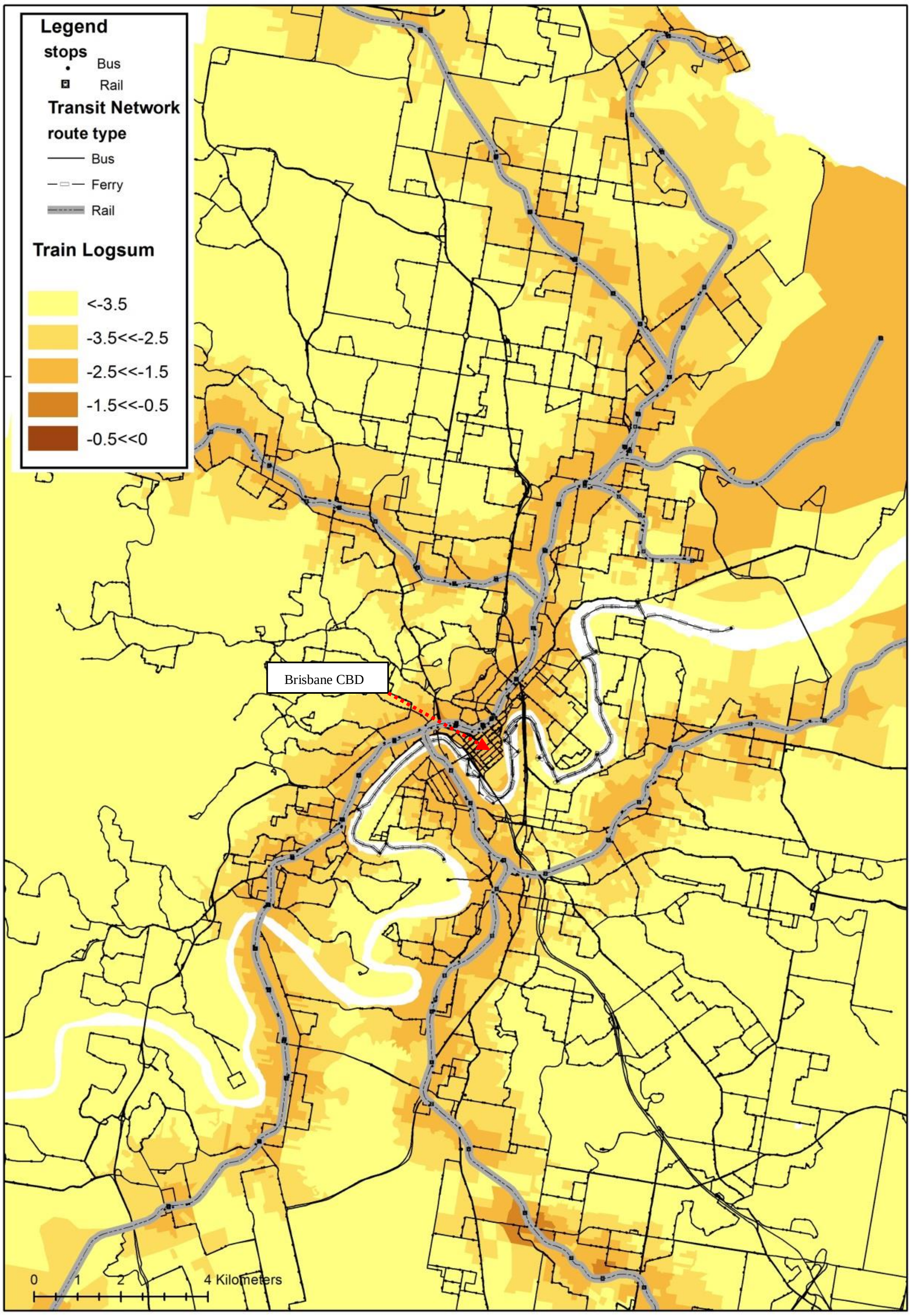


Figure 4-15: Estimated train logsum ($\omega_T^{od,\tau}$) to access the Gold Coast CBD (departing at 7:00 am)

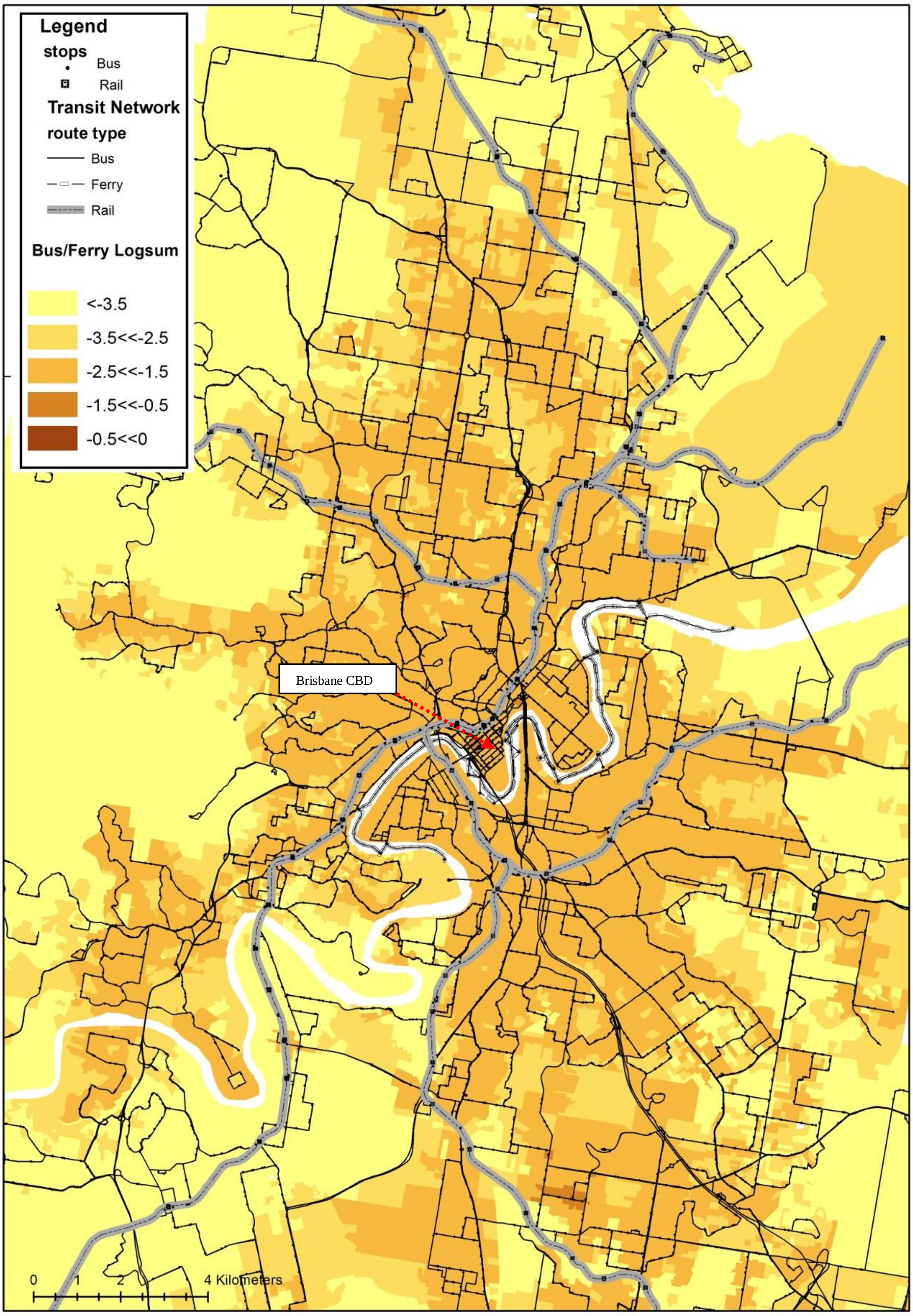


Figure 4-16: Estimated no-train logsum ($\omega_{NT}^{od,\tau}$) to access the Gold Coast CBD (departing at 7:00 am)

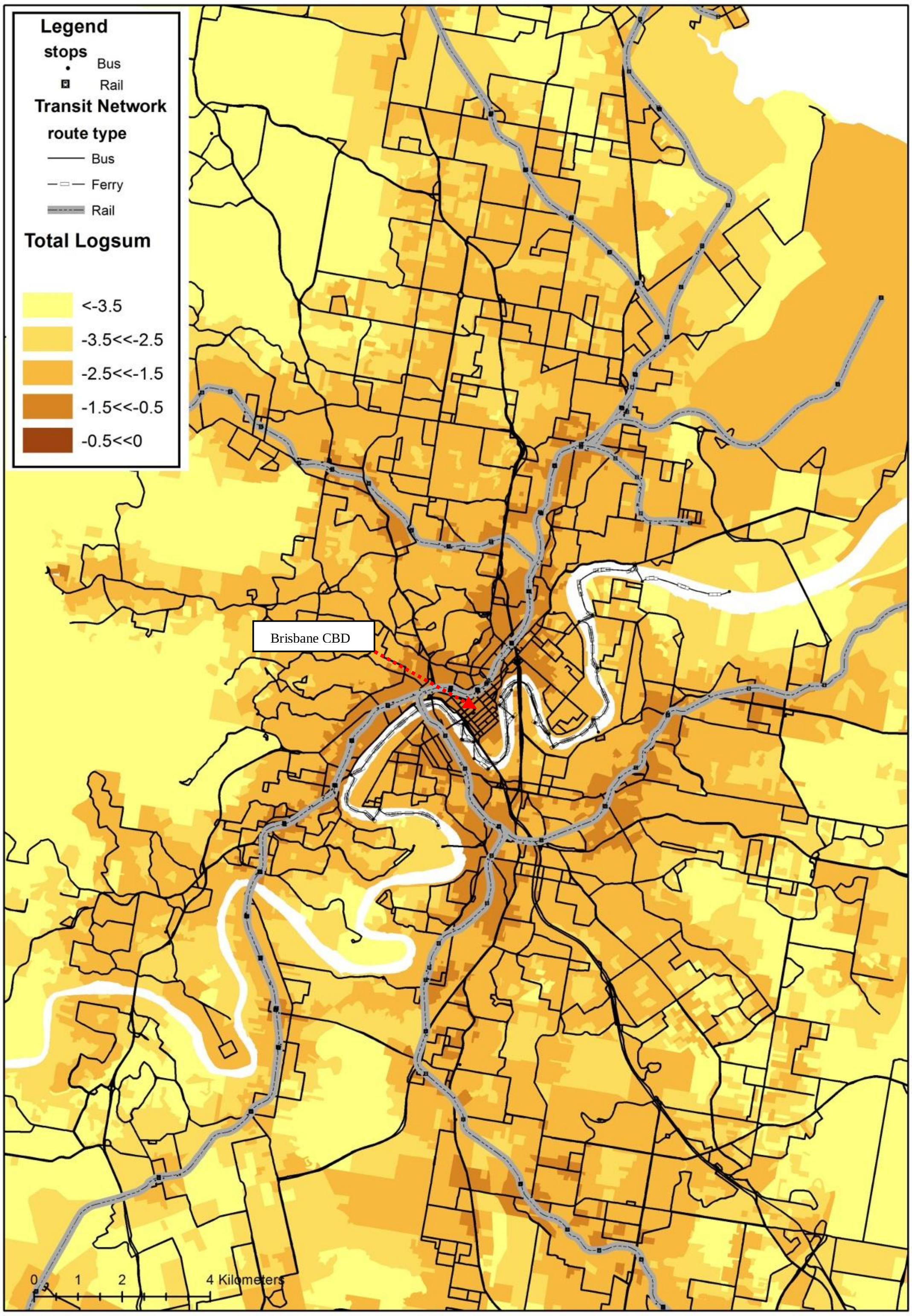


Figure 4-17: Estimated combined logsum (I_{od}^{τ}) to access the Gold Coast CBD (departing at 7:00 am)

The high level of logsum utility for combined transit service that is observed in Figure 4-17 as compared to Figure 4-15 (only train logsum) and Figure 4-16 (only bus and ferry logsum) shows the diversity of available modes to travel to Gold Coast CBD during the morning peak and again confirms that how the transit users consider a positive utility to diversity of available alternatives. As illustrated in Figures 4-15 and 4-16, the logsum values of the bus/ferry nest for the services provided by bus and ferry to the Gold Coast CBD are relatively greater than the logsum values for train only services. This observation again confirmed the diversity of options available by the bus/ferry nest, compared to the train nest to Brisbane CBD as a mandatory transfer point and also to Gold Coast CBD as the actual destination.

Also, similar to the observation for access to the Brisbane CBD, it appears that train services (Figure 4-15) are less sensitive to distance to destination in comparison with bus/ferry services (Figure 4-16) and the combined transit services (Figure 4-17). This can again be observed due to the high speed of the train network in comparison with bus/ferry services.

In order to incorporate the transit fares into logsum accessibility to the Gold Coast CBD, the adjusted logsum accessibility is calculated based on the 13AUD/hr value of time (VOT) and the departing time at 7:00 am weekday. These adjusted logsum values are plotted in Figure 4-18. As expected, and as easily observed from Figure 4-15, the adjusted accessibility value, A_{od}^{τ}, for all mesh blocks is significantly smaller than the original calculated logsum ,I_{od}^{τ}. This reduction is more observable when compared with declining in adjusted accessibility to the Brisbane CBD. The fact behind this observation is the high cost of transit services from the Brisbane suburbs to the Gold Coast, which has a high negative impact on the actual accessibility of Brisbane residents to Gold Coast.

As anticipated from the structures of both the proposed model and of the transit network in SEQ, the general logsum values for accessibility to the Gold Coast CBD (Figure 4-18) are significantly lower than these values for accessibility to the Brisbane CBD (Figure 4-8). As shown in Figure 4-18, the few mesh blocks with relatively high logsum accessibility values (A_{od}^{τ}>-0.5) for accessibility to the Gold Coast CBD are mostly are located around the Brisbane CBD. Four possible reasons emerge: 1) Longer travel time to the Gold Coast CBD for almost all Brisbane areas (excluding the outer south suburbs) compared to travel time to Brisbane CBD; 2) Structure of transit network in SEQ forces transit users to have at least one transfer for travelling to the Gold Coast. These transit transfers cause a significant decline in the total logsum due to high disutility of transfers in the model; 3) Fewer number of available routes to travel from Brisbane suburbs to Gold Coast, compared to travelling to the Brisbane CBD which again reduces the total logsum in the model; 4) The higher cost of travel between Brisbane suburbs and Gold Coast compared to travelling to the Brisbane CBD.

Examining the proposed transit network accessibility model by an only-travel-time accessibility approach (accessibility to Gold Coast CBD)

To demonstrate the advantage of the proposed accessibility model, compared to the existing only-travel-time models, the fastest travel time to Gold Coast CBD, T_{od}^{τ}, is calculated by the TBSP algorithm for all greater Brisbane mesh blocks (see Figure 4-19). In order to make this comparison easier, colour coded values for the travel time graph and the adjusted logsum graph are sorted in the same order increment.

As shown in Figure 4-19, using the travel time as the only attribute for estimating the network impedance could not capture the actual passengers' perception of the disutility of travel through the transit system. For example, a number of suburbs, particularly in the southern Brisbane area, are identified with approximately identical travel time (between 130 and 150 minutes) to the Gold Coast CBD; however, the adjusted logsum (A_{od}^{τ}) ranges from about -2.5 to about -4.5 for these areas. This observation indicates different levels of available transit services in these suburbs as well as various ranges of walking distances to the stops, which cannot be captured by the estimated travel time to destination alone. As a result, visualising the logsum values for the case study not only highlights the advantages of the proposed model, but also emphasises the importance of capturing transit users' perception about spatial-temporal transit characteristics (e.g. number of transit transfers, transit fare, number of available routes) and travel option diversities (both in-nest and cross-nest) in a real network.

To validate the effectiveness and robustness of the proposed logsum estimation, the following section presents a validation test using land value data.

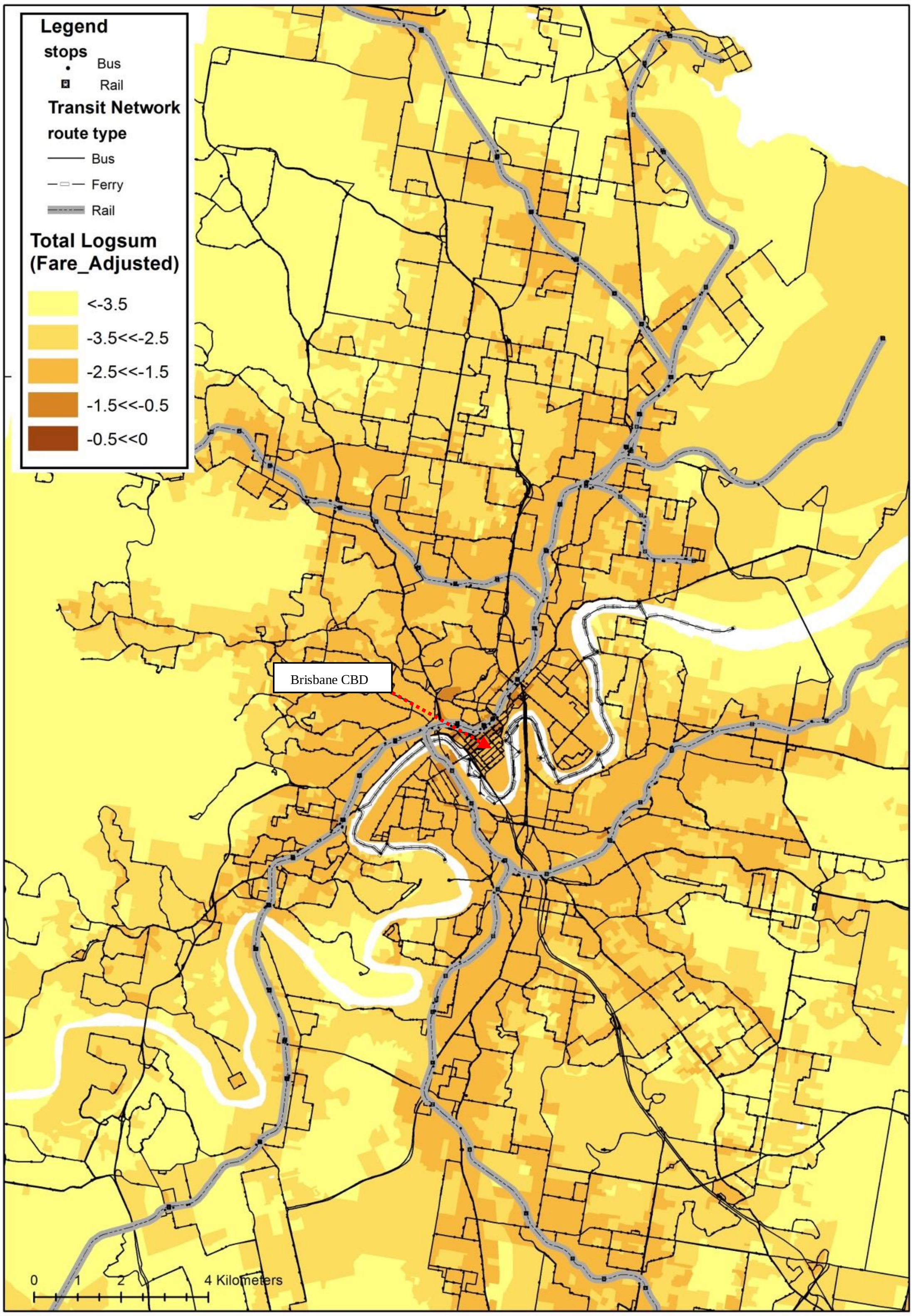


Figure 4-18: Adjusted logsum (A_{od}^{τ}) to access the Gold Coast CBD (departing at 7:00 am)

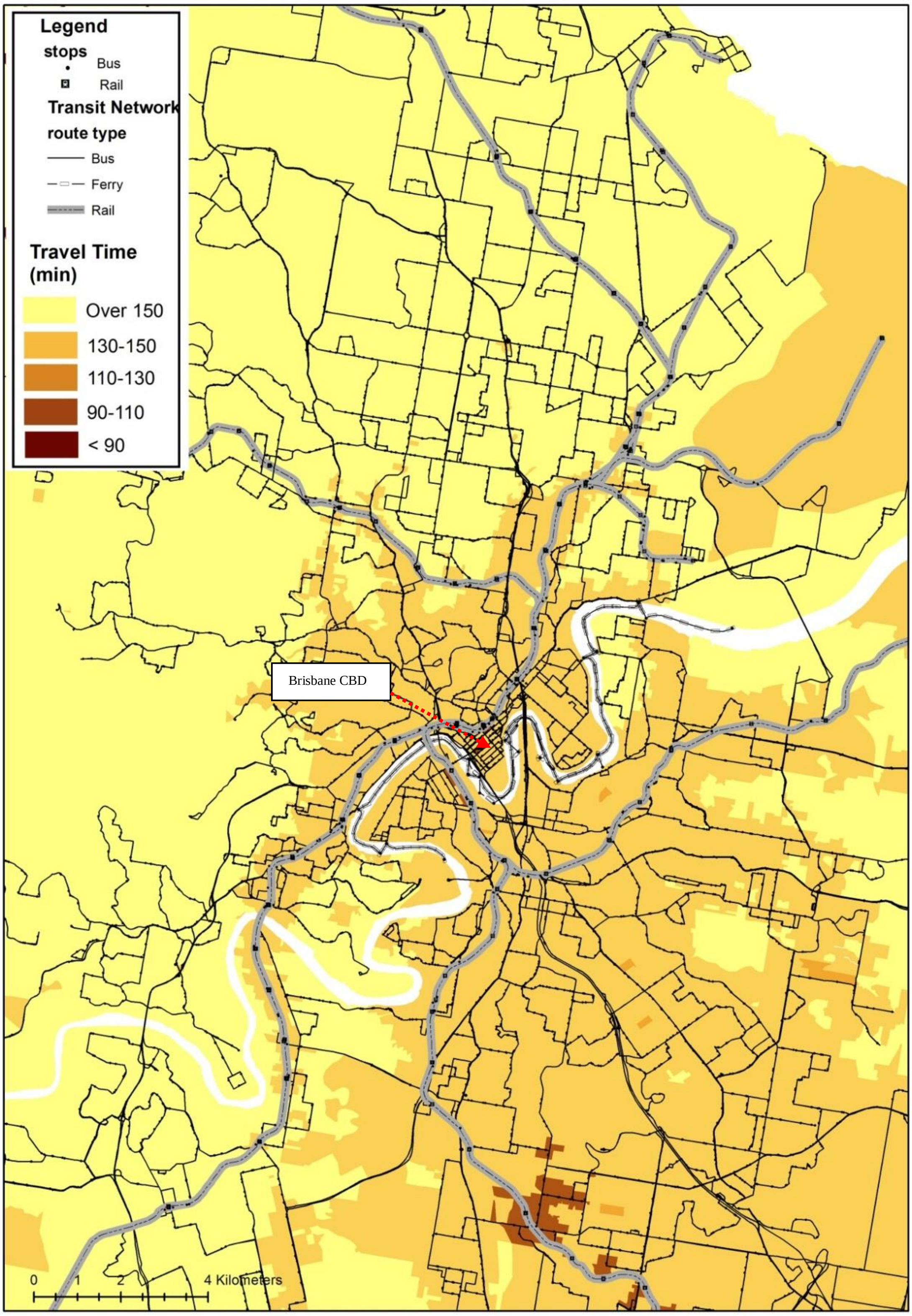


Figure 4-19: Fastest travel time (T_{od}^{τ}) to access the Gold Coast CBD (departing at 7:00 am)

4.4 LOGSUM ACCESSIBILITY VALIDATION BY LAND VALUE

The interaction between land use and accessibility, which has been extensively researched, has attracted increasing attention in recent years. It is well acknowledged that the location of land plays a key role in its preferences (Densmore & Mulley, 2012; Du & Mulley, 2007; Giuliano, Gordon, Pan, & Park, 2010), consequently affects its value.

Generally, accessibility to central business districts (CBDs) has a relationship with land value since the CBD and neighbourhood areas to CBD tend to have large amount of activities (e.g. employment) and hence they have higher land value (Iacono & Levinson, 2011a).

As a result, one of the most important factors people consider when choosing their preferred locations in the cities is accessibility to CBDs. Accessibility by public transport plays an important role as it provides equality of access to all residents.

The majority of studies on the land value and accessibility revealed that there is a linear correlation (Cao & Hough, 2012; Hess & Almeida, 2007; Mulley, 2014; Tsai, Mulley, & Clifton, 2012) or a linear correlation in the logarithms of dependent variable (Ai, 2005; Nurlaela & Pamungkas, 2014) between the land prices and accessibility. This strong statement allows us to use the land value as a tool to validate the output of the proposed logsum model. Examination of the relationship between land value and transit accessibility in the case study is explained in the following section.

Validating the logsum output by land value in the case study

For validating the logsum estimation systematically, thirty suburbs with high residential populations (over 10 persons/ha) were randomly selected as the case study, and the unimproved residential land price data for these suburbs was extracted from RP data (Real Property Database). RP data (RP-Data, 2014) is the most accurate and broad property database in Australia. The unimproved value of land in the market shows the value of land under normal sales conditions on which no structural developments have been made to improve the land price. This unimproved land value is used as a base to calculate local government rates and land taxes (DNRM, 2014).

As shown in the Figure 4-20 and Table 4-2, these selected highly populated suburbs (ABS, 2015a) are located with various geographical distributions from the CBD: fourteen within 5 km (radial distance) from the CBD, ten are between 5 and 10 km from the CBD, the rest are located over 10 km from the CBD.

Since RP data provides the unimproved land validation data at the parcel level, the residential land price for 54814 parcels for 2013-2014 was extracted from the database. Generally, the land values reflect to changes in surrounding areas (e.g. accessibility improvements) with a little time lag (Iacono & Levinson, 2011b; Nanda & Yeh, 2014). This makes the extracted land value data acceptable to use with 2009 accessibility results. Table 4-2 presents the suburbs' residential parcel numbers and their distance from the CBD.

Table 4-2: Number of residential parcels and geographical distribution of suburbs from the CBD

Suburb Name	Number of Residential Parcels	Euclidian radial distance from CBD (km)
Alderley	1686	5.8
Algester	2563	16
Annerley	2367	4.8
Auchenflower	1183	3.2
Carina	2702	7.1
Clayfield	2030	6.3
Everton Park	2736	9.4
Grange	1387	4.6
Greenslopes	1931	5.4
Hawthorne	1322	3.8
Highgate Hill	1076	2.4
Holland Park	2696	7.1
Jamboree Heights	1184	14
Middle Park	1369	14
Moorooka	3064	7.2
Morningside	2298	4.8
Mount Gravatt	985	9.2
Newmarket	1243	4.4
Norman Park	1877	4.1
Nundah	1825	8.3
Red Hill	1630	2.9
Robertson	1109	12
Sherwood	1381	8.6
St Lucia	1481	4.3
Taringa	1254	4.8
Toowong	1810	4.1
Upper Mount Gravatt	2567	12.1
Westlake	3032	14
Windsor	1747	3.9
Woolloongabba	1279	3.8

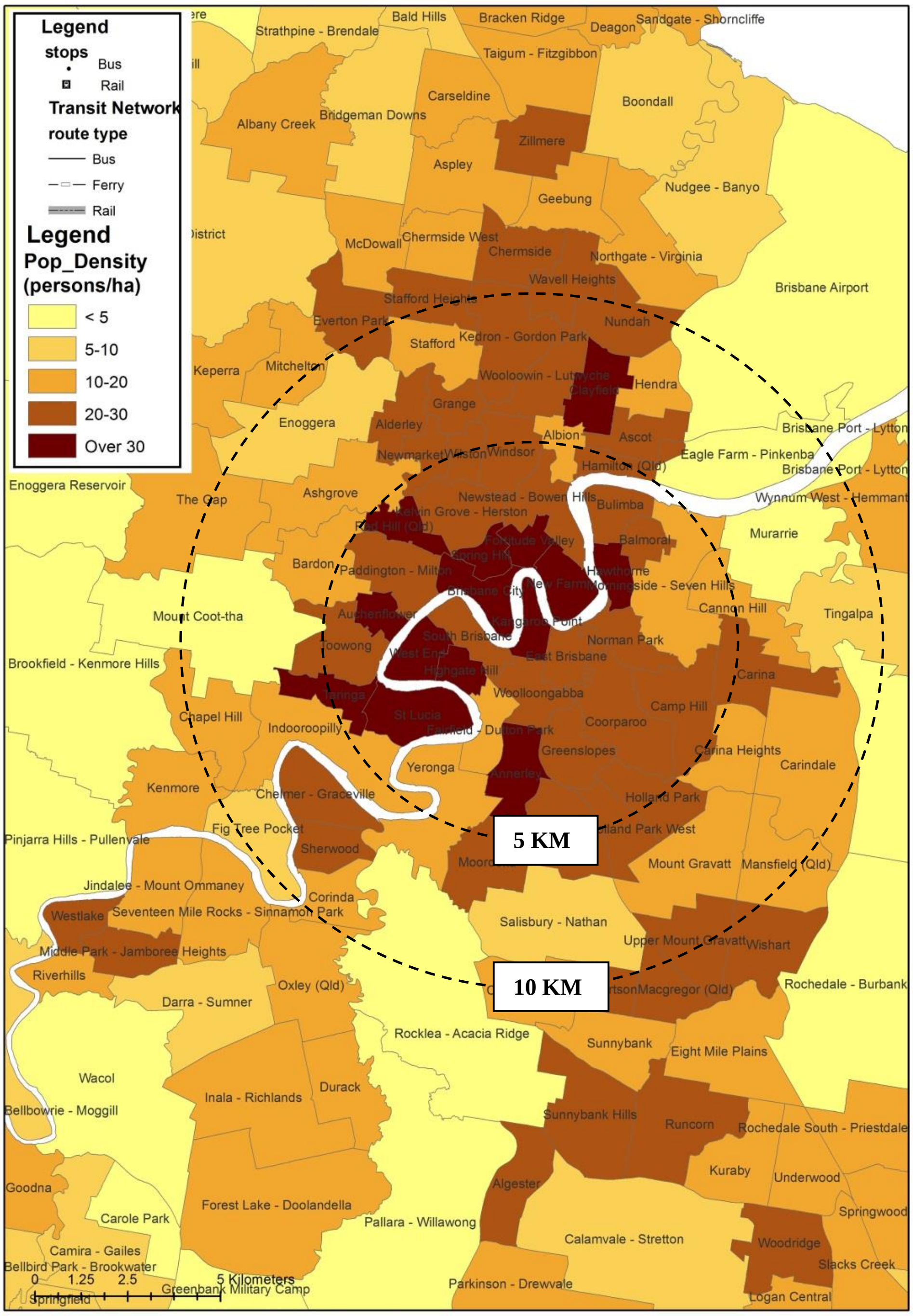


Figure 4-20: Population density of greater Brisbane suburbs

Cleaning the extracted dataset revealed that the land price for %1.23 of dataset (674 parcels) has not been validated which were excluded from the analysis. To adjust the geographical level of the land value and the estimated accessibility, the average land values (AUS$/square meter) are calculated for the remaining observations in the level of mesh block. As a result, the average land values are calculated for 2597 mesh blocks in these thirty suburbs.

To match the parcel lot plan IDs in the RP database with the mesh block IDs in SEQ, this research used Digital Cadastral Database (DCDB) for SEQ, which matched the land value data with the accessibility results estimated in the level of the mesh block.

Figure 4-21 shows a scatter plot of the land value versus the adjusted logsum accessibility. At first glance, the scatter graph shows an exponential relationship between land value and estimated accessibility. To examine this hypothesis, an exponential bivariate regression analysis is carried out for this dataset, along with a linear analysis.

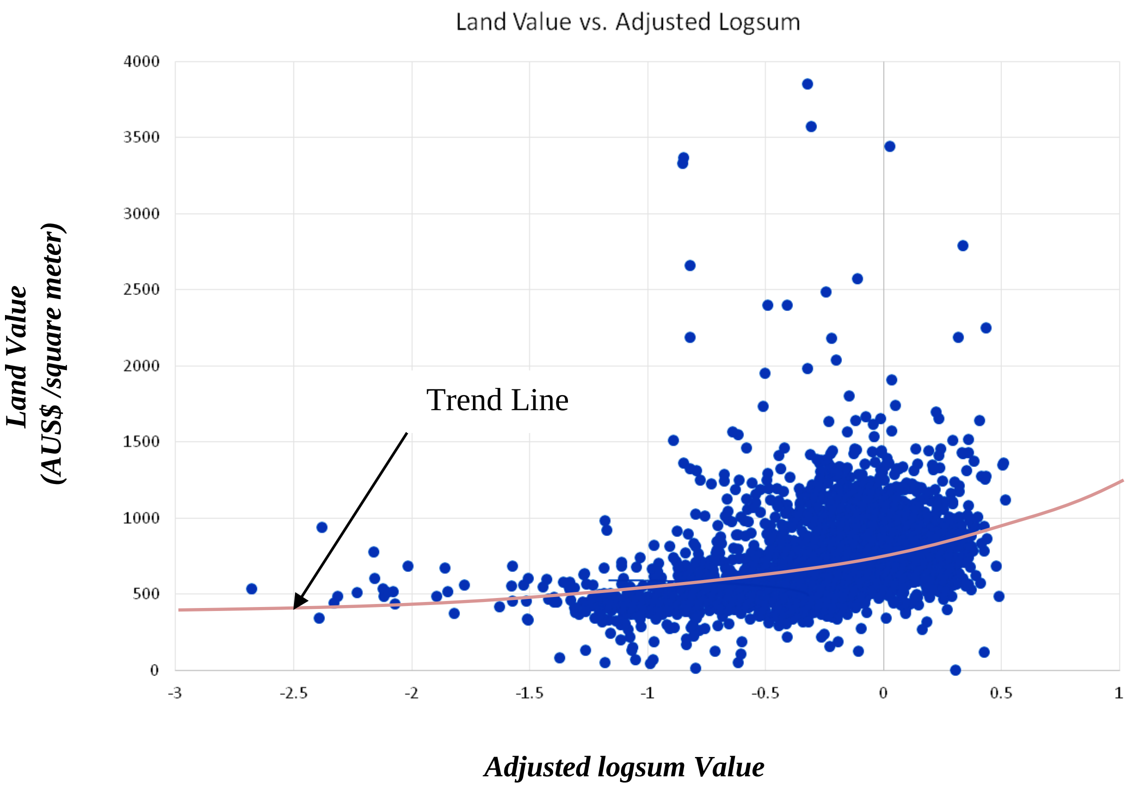


Figure 4-21: Land value vs. adjusted logsum accessibility

The bivariate regression model is used in this research in place of the multiple regression approach in order to remove all the other influences from other independent variables (e.g. socioeconomic status of residents), to focus only on the correlation between the land value and the accessibility estimations. The research used SPSS (Ver.16) for the regression analyses: the results of the simple bivariate linear regression model and exponential regression (linear regression with natural log of dependent variable) are presented in the Table 4-3.

Table 4-3: The results of the linear and the exponential regression models for adjusted logsum accessibility (independent variable)

Model	R	R Square	Adjusted R Square	Change Statistics		
				Std Error of the Estimate	Number of Samples	Significance (p-value)
Linear Model	0.354[a]	0.125	0.125	283.77	2597	.000
Exponential Model	0.425[a]	0.180	0.180	0.371	2597	.000

a. Predictors: (Constant), Adjusted_Logsum

The results of these two regression models confirm the hypothesis assumption regarding the correlation between the natural log of land value and the accessibility. As shown in Table 4-3, although the adjusted logsum appeared to be a significant variable ($P< 0.05$) in both regression models, there is significant improvement (%44) in the model fit (R-square) value of the exponential regression model in comparison with the linear model.

As noted earlier, the aim of this section is to validate the robustness of the proposed transit network accessibility model, compared to only-travel-time approaches. For this purpose, the fastest travel time for all the mesh blocks (in the case study) for travelling to CBD is extracted from the TBSP algorithm and is plotted versus land value in Figure 4-22. This figure also shows an exponential correlation between the land value and fastest travel time to CBD in a negative direction, drawn with a trend line.

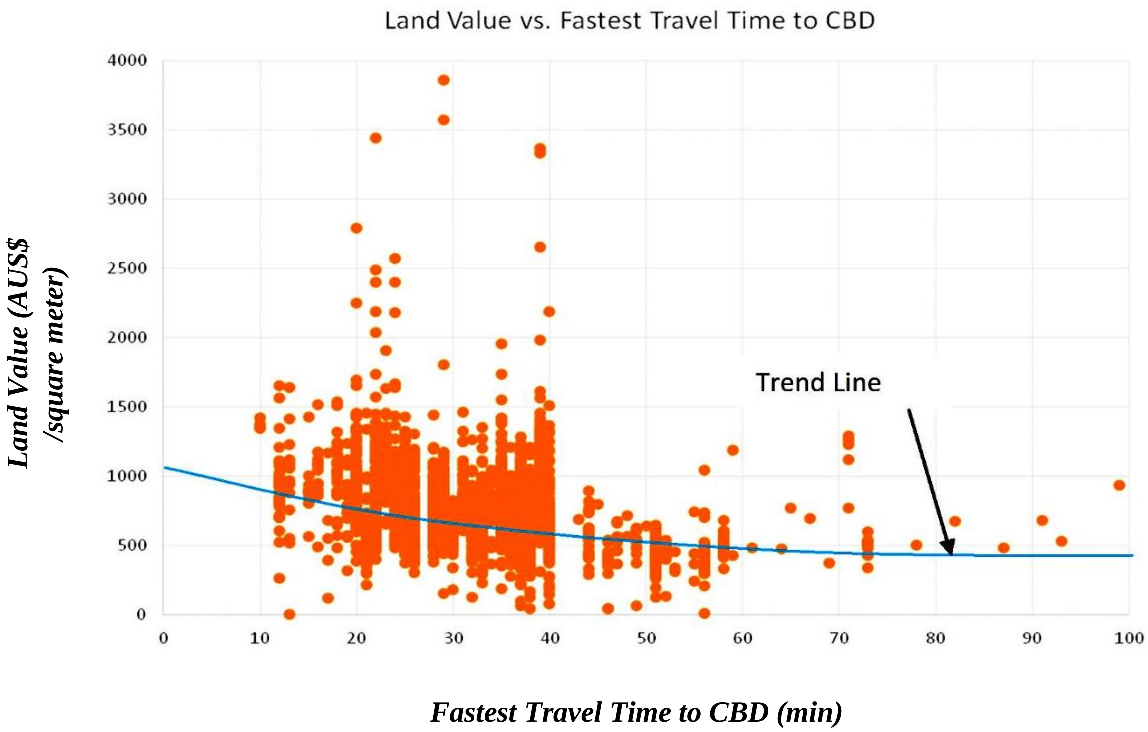


Figure 4-22: Land value vs. fastest travel time to CBD

As with to the regression analyses for adjusted logsum values, both linear and exponential bivariate regression analyses are carried out for the fastest travel time as an independent variable. The results are presented in Table 4-4.

Table 4-4: The results of the linear and the exponential regression for the fastest travel time to the CBD (independent variable)

Model	R	R Square	Adjusted R Square	Change Statistics		
				Std Error of the Estimate	Number of Samples	Significance (p-value)
Linear Model	0.330[a]	0.109	0.109	286.37	2597	.000
Exponential Model	0.365[a]	0.133	0.133	0.382	2597	.000

a. Predictors: (Constant), Fastest_Travel_Time

As shown in Table 4-4, comparing the model fit results for linear and exponential model again confirms that exponential bivariate analysis can provide a better prediction for estimating the land value.

Comparing the exponential regression analyses for adjusted accessibility value and for fastest travel time shows a significant improvement (over 35%) in the model fit (from 0.133 to 0.180) with the adjusted logsum accessibility values.

This observation shows that the estimated network accessibility model can provide more accurate prediction for the land value estimation, compared to that provided by traditional only-travel-time models. Based on the acknowledged statements about the relationship between land value and accessibility to city centres, we can conclude that the estimated logsum accessibility provides a better assessment of the actual accessibility of residents to CBD, which confirms the robustness and effectiveness of the proposed logsum accessibility model.

As a theoretical output, these results also highlight the importance of applying an accurate transit accessibility estimation technique for land value assessment models.

4.5 CONCLUSION

The results of the accessibility estimation for a real-sized transit network highlighted two more theoretical advantages of proposed model along with its' capability in capturing transit users' behaviour and network characteristics. First, the developed model is capable to highlight the benefits that the diversity of transit services (both "in-nest" and "cross-nest") can offer to the community. In other words, the model can capture the benefits which travellers can gain from all available services ("train" and "no-train" nests) in the transit network.

Second, using a random utility-based structure that estimates transit utility as a function of a diverse set of travel attributes calculated for a diverse set of path/mode options in the transit system can capture the stochasticity in perception of transit network among passengers. This approach can be a proper method for incorporating the stochastic error term that is accepted to exist in the developed utility function, since a similar algorithm is applied to generate the choice set for the choice model calibration and also accessibility estimation.

To highlight the robustness of the proposed logsum accessibility model, in comparison with time-dependent models, a bivariate regression analysis also has performed in this chapter. The results of this analysis validated the outcomes of model systematically and confirmed the model robustness and its' reliability. These analyses also highlight the importance of applying accurate accessibility models in the land value estimation approaches.

In the next chapter, several policy sensitivity analyses will be performed to understand and quantify the sensitivity of transit users to any changes in the transit system.

Summary of the chapter's contributions

Outcomes

- Capturing the benefits of transit diversity in perception of transit users
- Capturing the stochasticity and subjectivity of travellers in perception of transit network
- Emphasising the importance of considering the transit service characteristics in the model (e.g. number of routes, transit fare and number of transfers)
- Highlighting the importance of estimating the transit users' difficulties in travelling through the entire transit network (including "first-and-last mile" problem)
- Examining the robustness and reliability of the model in comparison with only-travel-time approaches
- Highlighting the importance of applying accurate transit accessibility measurements in the land value assessment models.

Key findings

- The sensitivity of transit users to the diversity of available transit alternatives is highlighted extensively when they have multiple choices in two different nests, compared to a situation when they have multiple options in only one nest (only train or only bus/ferry).

To underline the importance of this observation in the transit accessibility models, a policy sensitivity analysis also will be carried out in the next Chapter.

- Several mesh blocks were identified in the case study with a range of logsum accessibility values but with identical travel time. These examples can confirm the advantage and sensitivity of the proposed model in capturing travellers' behaviour and their perception about transit service characteristics, compared with only-travel-time accessibility measurements (e.g. fastest travel time to destinations or transit corridors).

- As a result of better geographical distribution of bus/ferry stops ("no-train" nest) and a higher number of available services for travelling with bus/ferry in the transit network, the general logsum of "no-train" nest is significantly higher than that of the train nest. However, due to faster in-vehicle travel time for the "train" nest, the minimum value of train logsum is higher than the logsum value for "no-train" (bus/ferry) services. These observations can be a motivation for performing more investigation to find optimal approaches for improving the accessibility in each mode of transit.

- Due to the zone based (distance-based) structure of the fare in the SEQ transit network, the effect of fares on the accessibility of suburbs located far from the CBD are more highlighted, compared with the areas located close to the CBD. This observation needs more attention from a policy maker's point of view as lower-income householders generally live in suburbs distant from the CBD and the higher costs of public transport for this group of people can reduce the desirability of transit services among them.

- Applying the estimated logsum as a predictor variable (independent variable) to the regression model for land value estimation improved the model fit by 35%, in compared to a situation when the fastest travel time is applied as an independent attribute (predictor). Due to accepted statements about the relationship between the land value and accessibility to CBD, this output can systematically validate the proposed logsum estimations.

Chapter 5: Model Sensitivities in Policy Analysis Applications

5.1 INTRODUCTION

Sensitivity analysis usually refers to the examination of the stability of a model when the model's attributes face of change and it is used to determine how changes in the output of model can be apportioned to changes in the different attributes of the inputs (Bonsall, Champernowne, Mason, & Wilson, 1977; Saltelli et al., 2008). Thus, the sensitivity analysis should determine how a model is sensitive either to change in values of the model's attributes or to change in the model structure (Pandian & Kavitha, 2012).

However, while such sensitivity analyses estimate the effects of the changing of attributes, they do not capture the policy change sensitivities. As a result, many researchers have proposed using policy sensitivity analysis to capture and quantify the model sensitivity to a policy change due to variations in the policy scenarios. The policy sensitivity analyses become very important when stochasticity and measurement error in a model makes the model analytically very difficult to identify optimal policies. Also, these analyses can be a useful tool for model simplification to produce more visible and understandable models and also, to support the decisions should be made by policy makers (Moxnes, 2005; Pannell, 1997).

The modeller may change, add or remove a designed restriction in order to examine a policy from the decision maker point of view. Alternatively, the modeller may define an objective (e.g. minimising or maximising the output). From the judgment of the decision maker, an optimal policy is the strategy which provides the optimal results (e.g. expected utility). It is assumed that the modeller knows the purpose of the decision maker and will be able to define different scenarios from his/her perspective (Pannell, 1997). By applying policy sensitivity analyses, the modeller can observe the value of the outputs for the defined strategies and also, the variation in values between the outputs of two strategies (e.g. between the optimal scenario and a particular scenario). After performing a preliminary analysis based on initial values, the modeller can revise the scenarios using the information obtained from the initial analysis (Bonsall, et al., 1977; Moxnes, 2005; Pandian & Kavitha, 2012; Pannell, 1997).

Existing research on transport planning, particularly accessibility planning, usually performed only a relatively limited number of runs. As a result, they could not observe the effect of policy changes and sensitivity of model attributes (Bonsall, et al., 1977). Reviewing the outcomes of Chapter 4 shows that highlighting the effectiveness of proposed model in this research needs more evaluation and investigation by performing a couple of policy sensitivity analyses.

For this purpose, to simulate realistic scenarios, this research extracted a number of scenarios from the proposed policies in South-East Queensland Regional Plan (SEQ Regional Plan 2009-2031) and Integrated Regional Transport Plan for South East Queensland (Connecting SEQ 2031).

One of the proposed policies in these plans is to expand the Morton Bay Rail Link from Petrie to Kippa-Ring. This new 12.6 km rail line will be completed by 2016 and it provides an express train service for the communities in Kippa-Ring and Redcliff area which currently they have only access to bus services (DSDIP, 2009; DTMR, 2010a).

Expanding the southern train lane to Richlands as part of the train expansion from Darra to Springfield is another scenario which is proposed to be investigated in this research. The train development to Richlands has been completed in 2011 and as a result, it can be considered as a proposed scenario for the model which has been developed based on 2009 transit network. Similar to train expansion scenario for Kippa-Ring area, Richlands' residents had not benefitted from any train services before 2011 (DSDIP, 2009; DTMR, 2010a). Analysing these two scenarios can also highlight the model sensitivity to capture the transit diversity at the mode level.

The SEQ regional and transport plan for 2031 also proposed to improve the Coast Link services from Brisbane suburbs to Gold Coast and Sunshine Coast. According to this proposed improvement, another scenario in this research is defined to examine the model sensitivity for facilitating the travel from Brisbane to Gold Coast area by removing a transit transfer.

Upgrading bus and rail stations, including extensive roll-out of new bus shelters is another proposed policy in SEQ plan for 2031 (DSDIP, 2009; DTMR, 2010a). The effects of this proposed improvement on the accessibility (from travellers' point of view) also will be investigated in this chapter.

Establishing the go card system and employer funded go card benefits (as part of salary sacrificing) for promoting a shift to public transport use is another proposed policy in SEQ-2031(DSDIP, 2009; DTMR, 2010a).This sensitivity analysis is performed in order to understand how these encouraging strategies can help to improve the transit accessibility in the perception of travellers.

Creating 15-minute walkable neighbourhoods (catchments) to public transit services is another proposed scenario in this research which is extracted from South-East Queensland Plan for 2031(DSDIP, 2009; DTMR, 2010a). The effects of this network improvement on the transit accessibility also will be examined in this chapter.

Thus, we can summarize the proposed scenarios for policy sensitivity analyses as:

1) Expanding the train lane to Richlands and Kippa-Ring areas
2) Improving the Coast Link Services from Brisbane to Gold Coast CBD by removing a transit transfer
3) Providing the shelter amenities for transit stops
4) Reducing the transit fares as a result of establishing the go card services and employer funded go card benefits
5) Creating 15-minute walkable neighbourhoods to transit stops.

Analysing these scenarios not only can help to highlight the sensitivity of model to different changes in the public transit system but also, can help to understand the value and effectiveness of these changes for improving the transit accessibility.

Consequently, these sensitivity analyses should answer the following key questions:

- How do transit users perceive the increasing of transit facilities (e.g. transit routes)?
- How can improving the transit services by providing express or direct routes improve the accessibility?
- How can providing shelters for transit stops improve the accessibility in the perception of transit users?

- How can reducing the public transport fares improve the value of transit accessibility in the perception of users?
- How can limiting the walking distances to transit stops improve the transit accessibility?

Chapter Outline

After these explanations about the policy sensitivity analysis and its application (5.1), the following sections propose five different sensitivity scenarios: Expanding the train lane to Richlands and Kippa-Ring areas (5.2.1), Improving the coast link services from Brisbane to Gold Coast by reducing a transit transfer (5.2.2), Observing travellers' perception about stop amenities improvement (5.2.3), Assessing transit users' sensitivity to transit fare changes (5.2.4), Observing the model sensitivity by creating 15-minute walkable neighbourhoods to transit stops (5.2.5). Finally, section (5.3) provides a summary of the results of these sensitivity analyses.

5.2 POLICY SENSITIVITY ANALYSES

To highlight the capability of the model as a capable tool to capture the proposed changes in the transit network and also to understand the effectiveness of these improvement, the below scenarios are investigated in the following sections.

5.2.1 Expanding the train lane to Richlands and Kippa-Ring areas

Investigating the model sensitivities for extending the train services to Richlands and Kippa-Ring areas are two sensitivity analyses which are carried out in this section. As mentioned earlier, the Richlands train station has completed in 2011 to provide train services for the residents in this area. Similar to Richlands area, the travellers in Kippa-Ring are also served by only bus services at the moment as the proposed train lane for this area is scheduled to open in 2016 (DSDIP, 2009; DTMR, 2010a). Accordingly, examining the model for these train developments can highlight the model sensitivity to transit diversity at the mode level.

In the first scenario, the model sensitivity to train lane extension to the Richlands area is investigated. To make the results more realistic, this analysis used the current Translink schedule for the trips departing at 7:00 am from Richlands station to the

CBD (Translink, 2014b). The walking distances also are calculated using the current location of the station.

The results of this sensitivity analysis for the mesh blocks with reasonable access walk (< 2 km) to the station are summarized in the Table 5-1.

As shown in Table 5-1, although adding a “cross-nest” transit service improves the average of fastest travel time to the CBD by 14.8%, the improvements of total and adjusted logsums are very remarkable (47.1% and 41.8% respectively). These logsum improvements range from 36.2% to 100.1% depends on the walking distances from mesh blocks to the proposed station (see Figure 5-1).

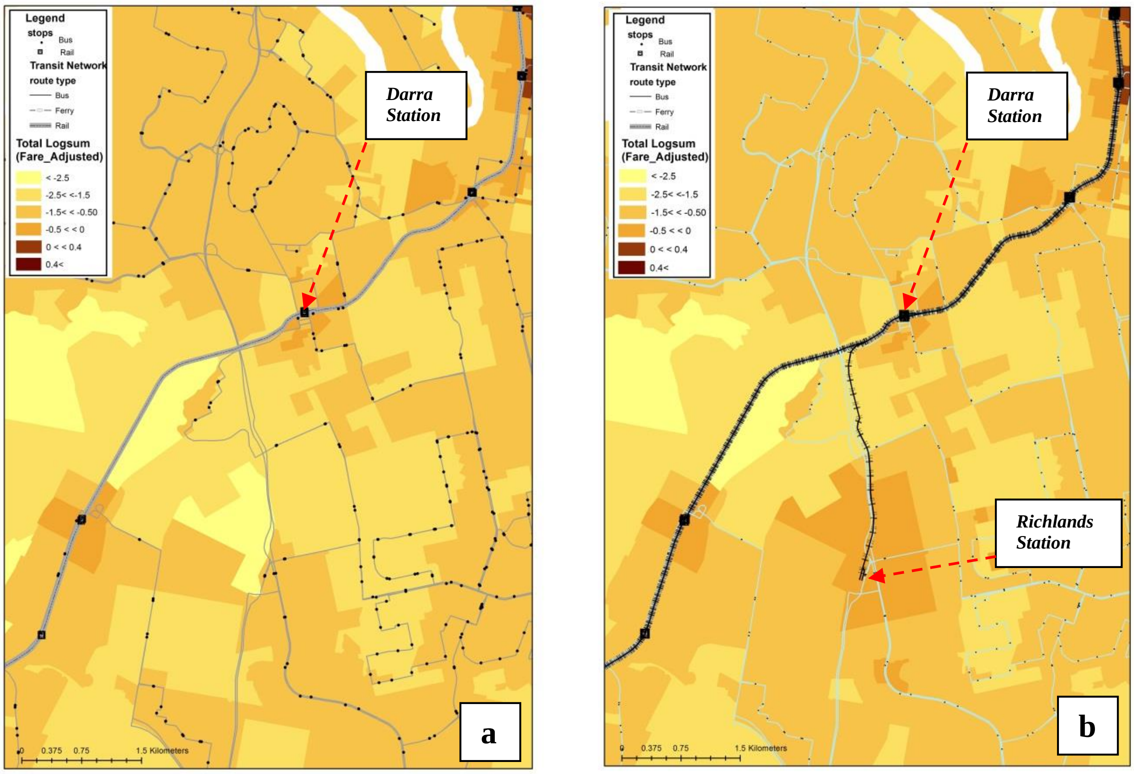


Figure 5-1: Fare adjusted logsum values before (a) and after (b) adding Richlands train lane to the transit network

Table 5-1: The results of the sensitivity analysis for Richlands area by adding a "cross-nest" transit service to the network

	Average of Bus Logsum	Average of Train Logsum	Average of Total Logsum	Average of Fare Adjusted Logsum	Average of Fastest Travel Time (min)
Before Changes	-1.293	N/A	-1.293	-1.456	72.79
After Changes	-1.293	-1.511	-0.684	-0.847	62.03
Improvement (%)	0.0%	N/A	47.1%	41.8%	14.8%

In addition, to examine the sensitivity of the model to "in-nest" improvements, a similar scenario defined to observe the travellers' perception about increasing the number of available stops (routes) in the network or "in-nest" improvements. In this new scenario, it is assumed that instead of adding the train services to transit network, the transport authorities can provide an express bus services with identical stop location, schedule and travel time to the CBD. The results of this sensitivity analysis are also summarized in Table 5-2.

Table 5-2: The results of the model sensitivity analysis for Richlands area by adding an "in-nest" transit service to the network

	Average of Bus Logsum	Average of Train Logsum	Average of Total Logsum	Average of Fare Adjusted Logsum	Average of Fastest Travel Time (min)
Before Changes	-1.293	N/A	-1.293	-1.456	72.79
After Changes	-1.151	N/A	-1.151	-1.314	62.03
Improvement (%)	11.0%	N/A	11.0%	9.8%	14.8%

As shown in the above table, although we can observe an improvement for the bus logsum (11.0%) and total logsum (9.8%) by adding this service to the bus network, the estimated accessibility shows more improvement for the diversity at the mode level ("cross-nest") in compare to this diversity at the stop (route) level ("in-nest").

Similar to the above scenarios, the model sensitivity to train expansion to Kippa-Ring area as a proposed plan in SEQ-2031 is also investigated in this section. The proposed train extension to Kippa-Ring area again can be interpreted as a "cross-nest" change in the transit system while the Kippa-Ring's residents are only served by bus services at the moment. To simulate the situation after train development in this area, the access walk distances for the mesh blocks within 2 km from the proposed location of the Kippa-Ring train station are calculated. For the schedule of proposed train services, it is assumed that the transport authorities can provide a train service every 15 minutes (from 7:00 am) from the Kippa-Ring station to the Brisbane CBD. The results of this sensitivity analysis for the mesh blocks with reasonable access walk (<2 km) to the station are summarized in the Table 5-3.

Table 5-3: The results of the model sensitivity analysis for Kippa-Ring area by adding a "cross-nest" transit service to the network

	Average of Bus Logsum	Average of Train Logsum	Average of Total Logsum	Average of Fare Adjusted Logsum	Average of Fastest Travel Time (min)
Before Changes	-1.373	N/A	-1.373	-1.555	99.51
After Changes	-1.373	-1.460	-0.706	-0.888	89.66
Improvement (%)	0.0%	N/A	48.6%	42.9%	9.9%

These outcomes can again highlight the advantage of the proposed model in capturing the transit users' perception about the diversity of transit services. While these results show that the average of fastest travel time in the model only is improved by 9.9%, the average of total and fare adjusted logsum are improved by 48.6% and 42.9% respectively.

Figure 5-2 also demonstrates the average of logsum (accessibility) improvement for the mesh blocks with reasonable access walk to Kippa-Ring train station.

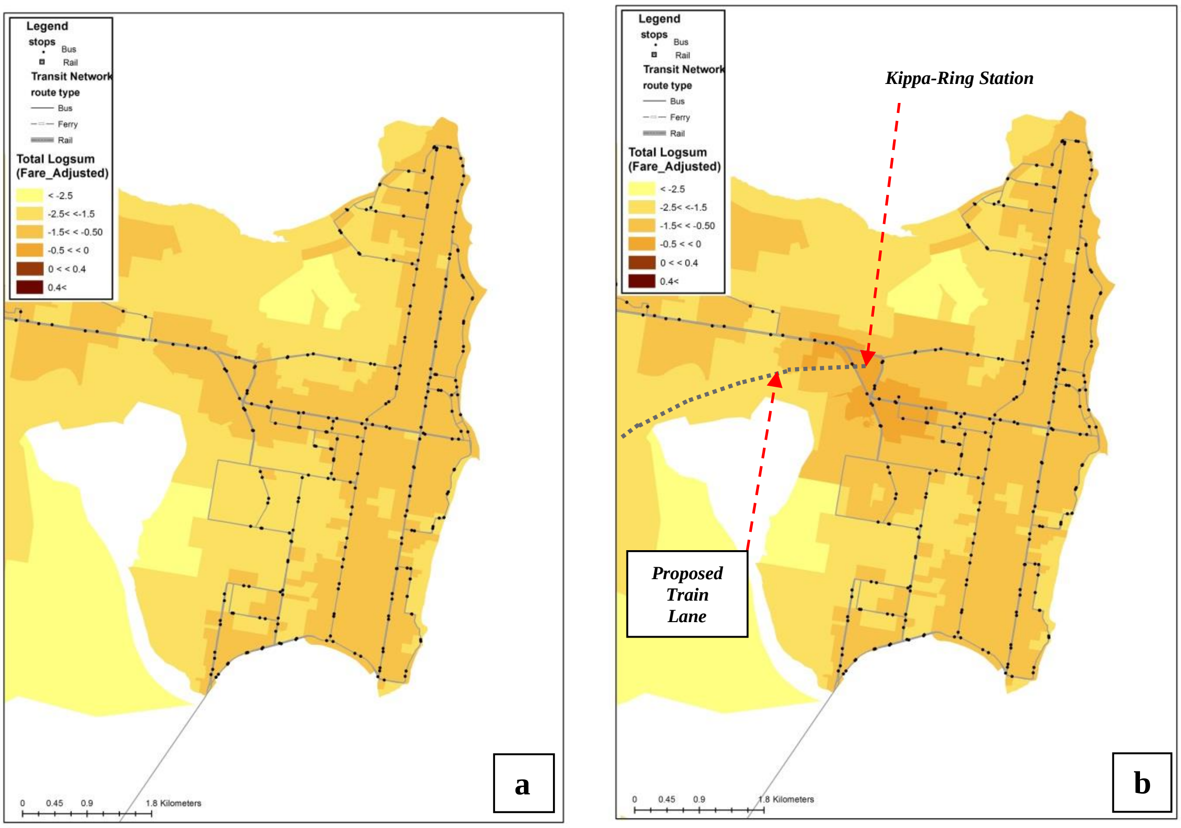


Figure 5-2: Fare adjusted logsum values before (a) and after (b) adding Kippa-Ring train station to the transit network

Similar to the defined "in-nest" scenario for the Richlands, the model sensitivity is also examined for the diversity of transit services at the stop level ("in-nest" changes). In other words, we simulate a situation which instead of providing the proposed train services, transport authorities can provide a new express bus service with similar schedule and travel time from Kippa-Ring station to the CBD. The results of this sensitivity analysis are summarized in Table 5-4.

Table 5-4: The results of the model sensitivity analysis for Kippa-Ring area by adding an "in-nest" transit service to the network

	Average of Bus Logsum	Average of Train Logsum	Average of Total Logsum	Average of Fare Adjusted Logsum	Average of Fastest Travel Time (min)
Before Changes	-1.373	N/A	-1.373	-1.555	99.51
After Changes	-1.188	N/A	-1.188	-1.370	89.66
Improvement (%)	13.5%	N/A	13.5%	11.9%	9.9%

Again as shown in Table 5-4, although the results of this “in-nest” development (adding a bus service to no-train nest) shows an improvement for the bus logsum (13.5%) and total logsum (11.9%), the sensitivity of transit users to the changes at the mode level (“cross-nest” changes) is significantly higher than these improvements at the stop(route) level or “in-nest” changes. These results also are consistent with the results of sensitivity analyses for the Richlands area and they revealed the capability of the model to capture the correlation between the utility error terms of the alternatives in a nest which decline the diversity benefits of “in-nest” changes in comparison with “cross-nest” improvements.

These results are very important as they can underline the value of transit diversity (particularly at the mode level) in perception of travellers, and highlight the importance of capturing these characteristics of transit network in the accessibility models. These outputs also revealed the more positive value that transit users give to providing the diverse transit services at the mode level rather than providing the fast (express) services in the transit network.

5.2.2 Improving the Coast Link Services from Brisbane to Gold Coast by reducing a transit transfer

This scenario is defined based on SEQ-2031 plan to examine the effects of coast line services improvement on the transit accessibility (DSDIP, 2009; DTMR, 2010a). For this purpose, Cannon Hill (a Brisbane suburb) is chosen as a case study in this analysis. The suburb is served by both “Train” and “no-Train” services (nests) in which more than 90% of mesh blocks in this suburb have reasonable paths to the Gold Coast by Train. However, all the travellers who depart at 7:00am from one of the reasonable train access stops (Cannon Hill, Morningside or Murarrie stations) to the Gold Coast, have to transfer the train lane at Park Road station to take another train (Beenleigh or Airport lines) to the Gold Coast.

In the defined scenario, to facilitate the travel form this suburb to the Gold Coast, it is assumed that the mandatory transit transfer at the Park Road station can be removed (see Figure 5-3).

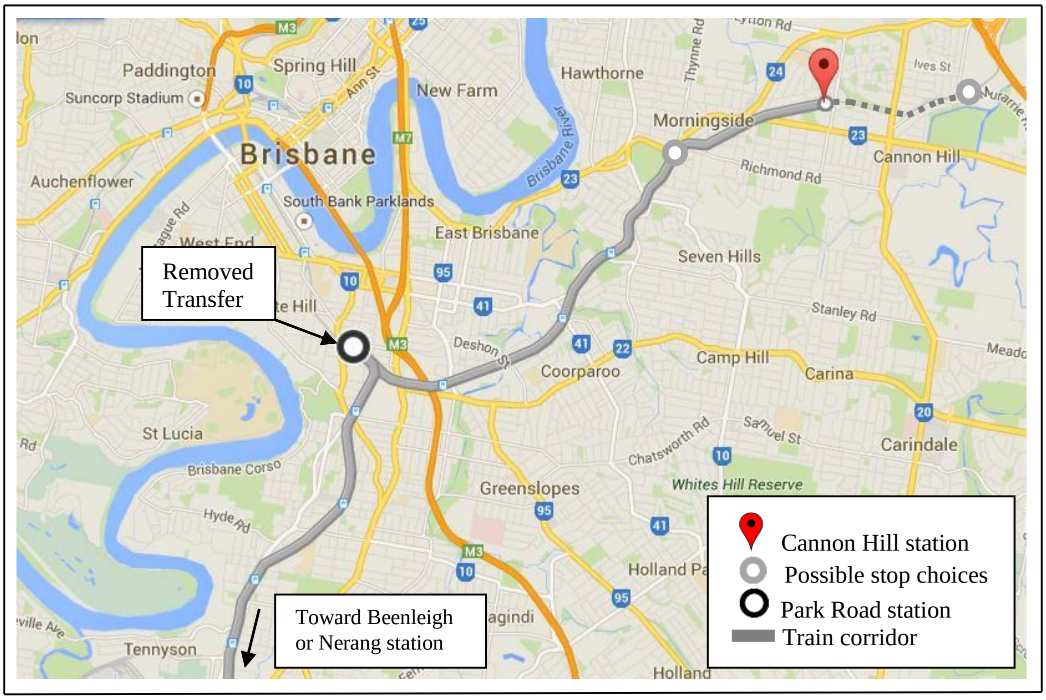


Figure 5-3: A schematic image for removing a transit transfer (GoogleMaps, 2015)

The outcomes of the logsum model for this scenario revealed an interesting observation. As shown in Table 5-5, as a result of this change in the transit network, the averages of the train logsum, total logsum and fare adjusted logsum for all mesh blocks with reasonable access to train stops are improved significantly by 14.7%, 11.7% and 11.0% respectively. These results also show that the average of fastest travel time from all mesh blocks of the suburb to Gold Coast CBD (by removing the associated waiting time for transferring) are improved by 8.5%.

Performing this analysis revealed that how transit users perceive the transit accessibility improvement as a result of this change in the transit system and also it can highlight the advantages of the proposed logsum model in comparison with only-travel-time estimations. The proposed model can estimate the perception of transit users about travel time improvement and also it can capture the positive perception of users in relation to providing more direct routes in the transit network. However, measuring the transit accessibility based on simple travel time measurements cannot capture the transit users' sensitivity and perception about actual difficulty of transfer in the transit network and consequently cannot estimate the transit accessibility accurately from travellers' point of view.

Table 5-5: The results of the sensitivity analysis for removing a transit transfer*

	Average of Bus Logsum	Average of Train Logsum	Average of Total Logsum	Average of Fare Adjusted Logsum	Average of Fastest Travel Time (min)
Before Changes	-2.199	-2.385	-1.697	-1.807	139.3
After Changes	-2.199	-2.035	-1.498	-1.608	127.4
Improvement (%)	0.0%	14.7%	11.7%	11.0%	8.5%

* for the mesh blocks with reasonable train paths to the CBD

5.2.3 Observing travellers' perception about stop amenities improvement

Evaluating passengers' perception about providing shelter amenities is another scenario which is defined based on suggested policies in SEQ-2031 (DSDIP, 2009; DTMR, 2010a) for examining the model sensitivity. In this scenario, it is assumed that proper shelter amenities can be provided for all transit stops at Eight Mile Plain (a Brisbane suburb). Based on transit facilities data that were provided by the Queensland Department of Transport and Main Roads (DTMR) in 2009, only 25.8% (32 out of 124) of stops with reasonable paths to CBD were equipped with a proper shelter in this suburb.

As shown in Table 5-6, the perception of travellers to this change in the transit system is positive; accordingly the average of total and fare adjusted logsum will be improved by 6.0% and 4.9% respectively. These logsum improvements for the mesh blocks range from 1% (for cases which already have access to several sheltered stops) to 33% (for cases which have access to fewer sheltered stops before improvement). Figure 5-4 shows a comparison of logsum improvement for 147 O-D pairs in the case study.

Table 5-6: The results of the sensitivity analysis for providing shelter for transit stop facilities

	Average of Bus Logsum	Average of Train Logsum	Average of Total Logsum	Average of Fare Adjusted Logsum	Average of Fastest Travel Time (min)
Before Changes	-0.648	-2.224	-0.638	-0.782	36.46
After Changes	-0.609	-2.224	-0.600	-0.744	36.46
Improvement (%)	6.0%	0.0%	6.0%	4.9%	0.0%

Performing this analysis revealed how transit users perceive the transit accessibility changes as a result of this improvement in the transit network. This analysis again confirms the advantages of the proposed accessibility model over traditional time-dependent models in capturing the perception of travellers about transit network characteristics.

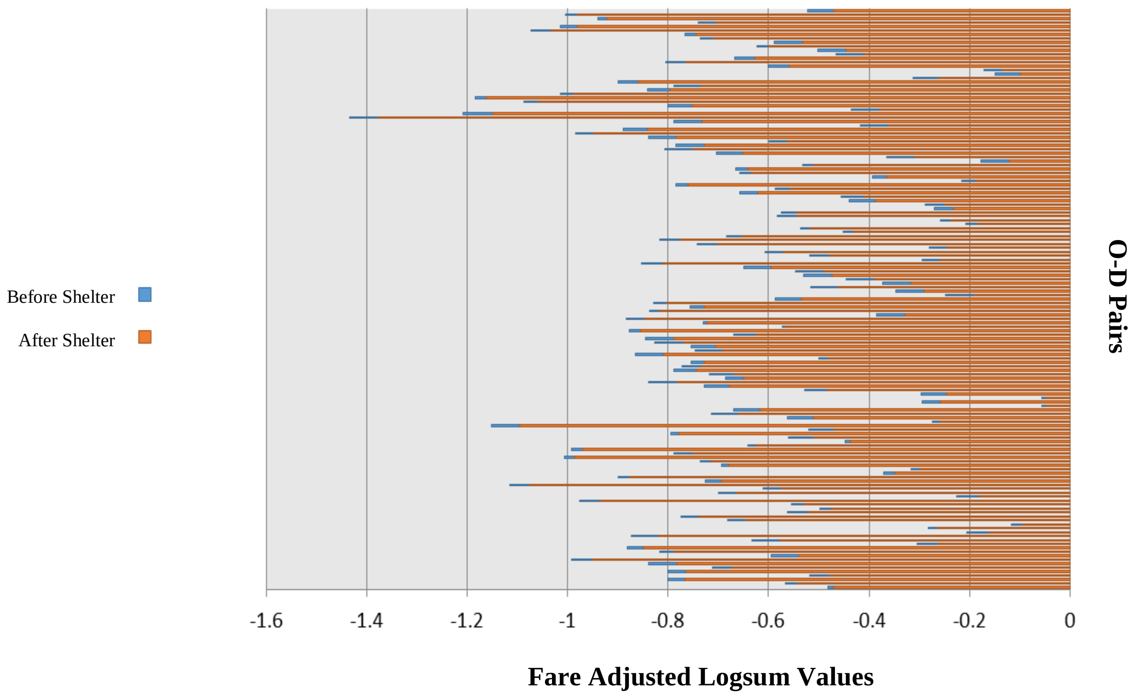


Figure 5-4: Fare adjusted logsum values before and after providing the shelter for stops (for each O-D pair)

5.2.4 Assessing transit users' sensitivity to transit fare changes

Observing the transit users' sensitivity to fare changes as results of establishing the go card services and employer funded go card benefits are two more policy sensitivity analyses which are examined in this research. Based on a study which has been carried out by DTMR, using the go card services can reduce each boarding time from about three seconds to 11 seconds. This time saving is about seven minutes on an average bus trip which can reduce the cost of the transit trip accordingly (DTMR, 2010a). To encourage the people to use go card instead of traditional ticketing system, based on the transit fare data in 2009, Translink reduced the go card fares up to 35% comparing to single paper tickets. Performing a sensitivity analysis based on go card fares shows that utilising go card system can improve the transit accessibility in perception of transit users by 2.8%.

To simulate a scenario for the salary sacrificing program which is suggested by SEQ-2031 (DSDIP, 2009; DTMR, 2010a), it is assumed that the transit fare can be reduced by 50% on average for travelling from/to all zones as a result of this plan.

The outputs of this sensitivity analysis for this scenario also show that adjusted logsum values for all SEQ mesh blocks can be improved by about 7.0% on average. These accessibility improvements may sound not too much, but travellers perceive these fare reduction policies positively and it can encourage travellers to shift to public transport use.

5.2.5 Observing the model sensitivity by creating 15-minute walkable neighbourhoods to transit stops

To facilitate the use of public transport, the SEQ-2031 proposed to create a maximum 15-minute walkable catchment area for accessing to transit services (DSDIP, 2009; DTMR, 2010a). To quantify the effect of this proposed improvement on the transit accessibility, McDowall (a Brisbane suburb) selected as a case study and it is assumed that SEQ transport authorities can redesign the transit network to maintain the maximum access walk for all access stops (with reasonable path to CBD) to 15-minute. For this purpose, all the reasonable paths for all the mesh blocks in the suburb are generated using TBSP algorithm and the maximum access walk to the stops are limited to 15-minute. All the mesh blocks in this suburb are served by only bus services in 2009 and on average around 40.2% of bus stops with reasonable paths to the Brisbane CBD (in the choice set) are located with more than 15-minute access walk from the centre of mesh blocks. Figure 5-5 demonstrates an actual example for a traveller's stop choice (for travelling to Brisbane CBD) before and after the network improvements.

This figure represents a situation that a traveller in the suburb has five different stop choices which for two of these choices, he/she should travel more than 15-minute for accessing to stops. As shown in this schematic graph, after redistributing and redesigning the transit network in the proposed scenario, these two stops should be relocated/rebuild to maintain the maximum access walk to 15-minute for the all reasonable transit routes to the CBD.

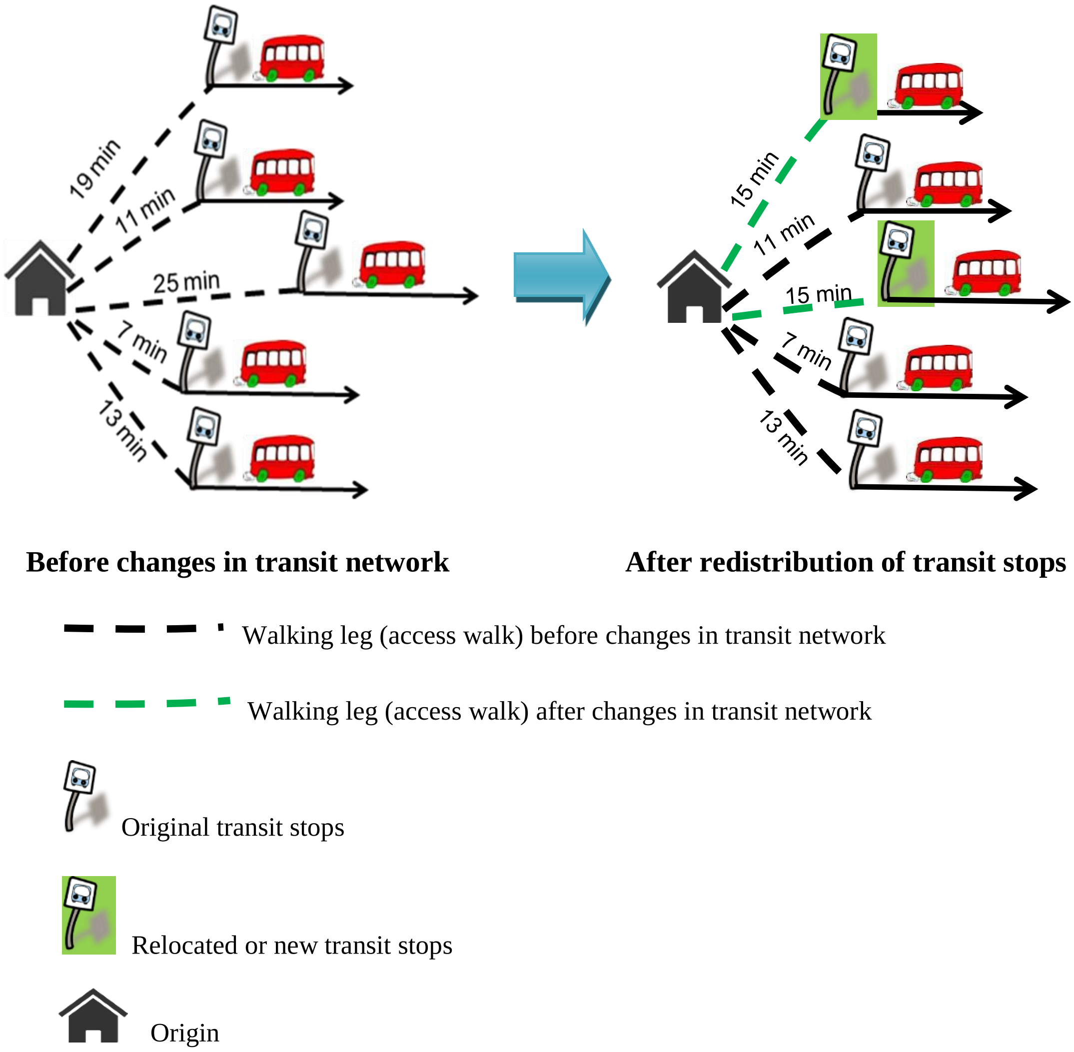


Figure 5-5: Defining a maximum 15-minute walkable neighbourhood catchment to public transit services

The results of this sensitivity analysis for this suburb are summarized in Table 5-7. To avoid computational complexity, this sensitivity analysis is based on an assumption that the schedule of bus services will not be changed due to this improvement. The outcomes of this analysis show that the average of total logsum and average of fare adjusted logsum are improved by 4.6% and 4.0% respectively. These logsum improvements for different mesh blocks in the suburb range from 0% (for cases without any stop choices with over 15-minute access walk) to 16.5% (for cases with several access stop choices with over 15-minute access walk). In other words, the transit accessibility improvement can be observed remarkably when the majority of stop choices in travellers' choice set are located with more than 15-minute access walk from the centre of mesh blocks.

Table 5-7: The results of the model sensitivity analysis for creating 15-minute walkable neighbourhoods to transit stops

	Average of Bus Logsum	Average of Train Logsum	Average of Total Logsum	Average of Fare Adjusted Logsum	Average of Fastest Travel Time (min)
Before Changes	-0.87	N/A	-0.87	-1.00	56.63
After Changes	-0.83	N/A	-0.83	-0.96	56.56
Improvement (%)	4.6%	N/A	4.6%	4.0%	0.1%

On the other hand, as shown in Table 5-7, the average of fastest travel time to CBD only improved by 0.1% because of this improvement. The reason behind this observation is that the routes with the fastest travel time between this suburb and Brisbane CBD do not necessarily have over 15-minute access walk. As a result, redistributing the transit stops by limiting the access walk to 15-minute for the all reasonable transit routes to the CBD cannot improve the fastest travel time from these mesh blocks to the CBD significantly. This travel time improvement can be only observed in the areas which they are not served by any stop choices (transit routes) with less than 15-minute access walk.

This observation can highlight the advantages of the proposed logsum accessibility model for capturing the transit infrastructure improvements. The logsum structure in the developed model can capture any changes in all available choices which cannot be highlighted in the traditional accessibility approach based on shortest-path estimations.

5.3 CONCLUSION

Reviewing the results of policy sensitivity analyses in this research highlight the ability of the developed model to use as a decision making tool for examining different policies in the pre-implementation stage and also in the planning stage. These results also revealed that the transit users give different values to different improvements and changes in the transit system that are not easy to predict without performing sensitivity analyses due to stochastic nature of travellers' behaviour.

Based on these analyses, we can conclude that; first, transit users give higher positive value to improvements at the mode level than to stop (route) level improvements. This outcome can be interpreted that investment on providing transit diversity at the mode level ("cross-nest" services) can improve the accessibility more significantly in compared to investing on providing diverse transit services at the stop level ("in-nest" services). These outputs also revealed the higher positive value that transit users give to transit service diversity (at the mode level) rather than creating express services in the transit network.

Second, travellers give a significant positive value for removing a transit transfer from the network. This observation can be very important from transport planners' point of view: providing more direct routes to attraction points, particularly during seasonal events, can encourage travellers to shift from other modes of transport to public transit services.

Third, the sensitivity analysis on providing transit amenities has revealed that travellers give a positive value for providing the shelter amenities at stops. This improvement is more significant when travellers' choices are limited to a few sheltered access stops in compared to a situation that travellers have access to numerous sheltered access stops in their choice set. This finding confirms that investment in providing the shelter amenities for the stops should be distributed as opposed to concentrated in only one area.

Fourth, the sensitivity analysis on the transit fare shows that users give a considerable positive value to the reduction of the cost of the trip. This observation can be very important from policy makers' point of view as Translink has announced that the transit fares in Brisbane are being increased every year by 7.5-15% (Translink, 2014a). Continuing this policy can reduce the desirability of using public transit for lower-income householders that generally are living in suburbs distant from the CBD and they are paying higher transit fare for travelling to attraction points (e.g. CBD). On the other hand, reducing the cost of the trip by applying the suggested policies in SEQ-2031 (e.g. salary sacrificing for transit users) can promote the travellers who benefitted from this plan to shift to public transport use and reduce the effects of current incremental fare policies.

Fifth, the results of sensitivity analysis for creating a maximum 15-minute walkable neighbourhood to public transit services showed that although the developed model can capture the model sensitivities to this change, the amount of this improvement is not much significant in comparison with other examined policies in the research. The accessibility improvement for this change can only be observed for the areas which they do not serve by any stop choices with under 15-minute access walk. This outcome is very important while the cost of these re-developments for transport organisations can be very expensive.

According to outcome of these policy sensitivity analyses, using the developed model as an accessibility measurement tool not only can help urban and transport planners to design the transit network more efficiently but also, it provides an opportunity to identify cost-effective (optimal) policies for improving the transit accessibility in post-implementation stage.

In the next chapter, the research outcomes will be summarised and a number of avenues for future research will also be explained.

Summary of the chapter's contributions

Outcomes

- Investing in providing the diverse transit services (at the mode level) can improve the accessibility more significantly, compared to investing in providing diverse transit services at the stop level ("in-nest" services) or even investing in providing express transit services
- Creating more direct routes (without transfer) can improve the accessibility and encourage travellers for modal shift towards public transport
- Investing in providing the shelter amenities for stops should be distributed in different areas as opposed to concentrated in only one area
- Reducing transit fare can encourage travellers, particularly lower-income groups, to travel with public transit
- Creating 15-minute walkable neighbourhoods to stops can only improve the transit accessibility remarkably when the majority of stop choices in the travellers' choice set are located with more than 15-minute access walk from the centre of mesh blocks.

Key findings

- Capability of the model to use as a decision making tool for:
    - Quantifying different policies and scenarios,
    - Evaluating the success and risk of different policies and;
    - Identifying optimum solutions for improving transit accessibility.

Chapter 6: Conclusion

6.1 INTRODUCTION

The overall aim of this thesis has been to improve the accuracy of transit network accessibility model by identifying and rectifying the shortcomings in the existing approaches. Most notably, we found that, due to the inherent complexities of public transport (e.g. the multimodality of services and the importance of strategic choices), developing an accurate transit accessibility model is challenging.

To manage these complexities, a rich body of research in the context of transit network accessibility has used simple distance or travel time to estimate transit accessibility to destinations. Although some research has also utilised utility-based measurements in their proposed approaches, these approaches to transit accessibility can be improved in the following possible directions:

1) To estimate the transit network accessibility for the entire transit journey (from origin to destination) and effectively capture significant attributes (e.g. travellers' behaviour, transit network characteristics) that affect the utility of travel in time-dependent and complex transit networks;

2) To capture the effect of transit route and mode diversities in the network; and;

3) To consider the travellers' subjectivity in the transit network.

As a result, the key goals in this research were to develop a more accurate transit network accessibility model by capturing travellers' behaviour, diversity in preferences and their stochasticity in perceptions of transit network as well as fine details of spatio-temporal characteristics of transit system.

In this chapter, a summary of the main findings (6.2), including the common limitations of existing accessibility models (6.2.1) and the limitations of existing transit accessibility models (6.2.2), is presented first. Then, significance of the research is explained in section (6.3). The theoretical and practical contributions of this research are then summarized in (6.4.1) and (6.4.2) respectively. Section (6.5), provides a summary of individual chapters' contributions, following by the research limitations (6.6). New avenues are suggested for future research in the final section (6.7).

6.2 SUMMARY OF MAIN FINDINGS

6.2.1 Common limitations of existing accessibility models

The literature review of existing accessibility models revealed that existing models dealt with the following limitations:

1) Collecting and preparing data for the modelling:
    - Obtaining high resolution data sets
    - Using different type of geo-coded data sets (e.g. census data, household travel survey data, land data)
    - Using different type of data sets which surveyed in different time
    - Requiring subjective data sets (e.g. for modelling the travellers route choice behaviour)
    - Obtaining qualitative data.
2) Estimating the appropriate travel impedance:
    - Ignoring travellers' behaviour in estimating the impedance of network
    - Disregarding fine details of transit network characteristics in estimating the travel impedance.
3) Ignoring travellers' choices and preferences in the transport network:
    - Applying single route approach (e.g. the route with minimum travel time or shortest distance).
4) Estimating the destinations' attractiveness:
    - Applying quantitative approaches (e.g. number of employees or number of available car parks in destination) for weighting the opportunities.
5) Aggregating the accessibility outputs without any robust theoretical approach:
    - Aggregating the modes of travel and disregarding various contributions may be provided by each mode of travel.

6.2.2 Shortcomings in the existing transit accessibility models

The main limitations and drawbacks to the existing transit accessibility models can be summarised as follows:

Ignoring travellers' behaviour and fine details of transit network characteristics

Due to the complexities of public transit system, the impedance element of the existing transit accessibility models is mainly represented by the utility of attributes for accessibility to transit corridors (transit stops) or represented by only a simple travel time to actual destinations. As a result, the existing transit accessibility models could not capture the fine details of transit service characteristics and travellers' behaviour in the entire transit network.

Ignoring transit users' preferences and their stochasticity in the transit network

The existing transit accessibility models do not aim to consider travellers' preferences and their stochasticity in the perception of transit system; focusing on only a single path to destination for accessibility estimation. These approaches assumed that all the travellers have similar objectives (e.g. minimum travel time for reaching to transit stop or actual destination) and they also able to find the best alternative to destination.

Reviewing the transit route assignment techniques and transit route choice models also revealed that a number of researchers (Fonzone & Bell, 2010; Kurauchi, et al., 2012; Schmöcker, et al., 2013) acknowledged the importance of travellers' preferences and developed transit assignment models to consider transit users' choice behaviour. However, these approaches has not been utilised in the transit accessibility models as they have two major drawbacks: first, the existing transit assignment approaches captured only the travellers' path choices from given departure stops and ignored access legs from the origin to the transit network. Second, generating hyperpaths for all strategies in the real-sized transit networks is very difficult, if not impossible. Several researches also aimed to capture stochasticity and subjectivity of travellers in the transit system, but they either focused on subjectivity for choice of destinations (e.g. parallel conductance and LUPTAI models) or aimed to capture stochasticity of the transit services only.

6.3 SIGNIFICANCE OF THE RESEARCH

The main significance of the research can be summarised as follows: First, a transit accessibility model is proposed which is capable of capturing the travellers' behaviour throughout the entire transit journey from origin to destination. The developed discrete choice model in this research is based on choice of transit access stops which also allows us to understand and capture behavioural aspects of transit users and fine details of transit characteristics in the real-sized transit network. The results of the choice model show that the choice of access stop is affected not only by the attributes of network impedance from the stop to the destination (e.g. access walk), but also, significantly, by the stop characteristics itself, such as number of available routes at the access stop, mode of transit and shelter availability.

These results also revealed that, contrary to conventional approaches in the transit accessibility, travellers perceive the transit network by attributes other than only fastest travel time to destination. For example, the results of the choice model showed that the disutility of transit transfer and access walk to stops in perception of travellers are respectively 31 times and 7 times more important than fastest travel time from access stop to destination. These outcomes can highlight why current transit network accessibility approaches based on only fastest travel time are failed to capture the real impedance of transit network and consequently they cannot provide accurate accessibility estimations. While, the goal of an effective accessibility measure is to quantify the actual perceptions of passengers in accessing urban facilities, applying the proposed behaviour-based model which incorporates the actual passengers' behaviour can highly improve the accuracy of accessibility measurement.

Second, the developed model is capable of highlighting the benefits that the diversity of transit services (at the stop and mode level) can offer to the community. In other words, the model can capture the benefits which travellers can gain from all available transit services in the transit network. This advantage of the model is very important while the results of sensitivity analyses revealed that transit diversity at the mode level can improve the accessibility by around 40% in perception of transit users.

Third, the developed model is capable to capture stochasticity and subjectivity which it is acknowledged to exist in the perception of transit network among travellers. In general, different travellers have different preferences in the transit network and they may choose various paths to destination in different situations. The results of analysis on the output of choice model revealed that over 57% of travellers did not choose the paths with the highest estimated utility and also over 50% of them did not choose the paths with the highest estimated probability in the choice set. However, reviewing the existing accessibility approaches showed that they generally ignore the travellers' choices in the transit system by utilising the shortest path approach to estimate the impedance of network. These models assume that all the travellers have perfect knowledge in the transit network and they choose the best route to the destination which it is a strong assumption. The developed model in this research is capable of capturing the indeterminacies in perception of transit network among passengers by estimating a combined transit network utility as a function of a diverse set of travel attributes calculated for a diverse set of path/mode options in the transit system. While a similar algorithm is applied to generate the choice set for the choice model calibration and accessibility estimation, this can be a proper method for incorporating the stochastic error term that is accepted to exist in travellers' behaviour.

In addition to the mentioned model significance, the developed model can be practically utilised by urban and transport planners as a decision-making tool to quantify different policies and identify optimum solutions for improving the transit accessibility.

6.4 SUMMARY OF THEORITICAL AND PRACTICAL CONTRIBUTIONS

The theoretical and practical contributions of this research can be summarised as follow.

6.4.1 Theoretical contributions

This research had several main novel theoretical contributions:

- Proposed a choice model at the stop level, which solves the problem with accurate prediction of path choices due to passengers' strategic boarding/alighting behaviour in high frequency transit networks
- Developed a framework to capture the behavioural aspects of transit users and the spatio-temporal characteristics of the transit system.

- Highlighted the diversity benefits that transit users can gain from the availability of a diverse set of paths or transit mode options in the transit network.
- Captured the stochasticity in the perception of transit network among transit users.

Along with these key theoretical contributions, this research also had the following contributions:

- Rectified the correlation between available transit mode services
- Rectified the correlation among the path alternatives (path overlapping problem) at the stop level.

6.4.2 Practical contributions

The following points were found to be practical advantages of the proposed model:

- The developed model can be used as a decision-making tool for urban planning organisations (e.g. local city councils) and transport authorities (e.g. Department of Transport and Main Roads) for evaluating the risk of different transit projects in the planning stage and also for identifying optimum policies for improving the transit accessibility
- The proposed methodology also can also apply to passengers' behaviour analysis in transit networks and transit network modelling research.

6.5 SUMMARY OF INDIVIDUAL CHAPTERS' CONTRIBUTIONS

In this section, a brief outline of the outcomes and limitations of the research is broken down to each individual chapter.

6.5.1 Chapter 2: Literature Review

Outcomes

- Exploring the weaknesses and limitations of existing accessibility models, particularly transit accessibility models
- Clarifying the importance of incorporating the multiple high-utility paths
- Exploring the advantages and limitations of route set generation techniques and route choice approaches
- Evaluating the major shortcomings of the current path choice approaches.

Limitations

The major limitations with the existing transit path choice approaches are:

- Focusing on travellers' choices from given departure stops
- Limiting the size of the path choices that is handled by the travellers.

6.5.2 Chapter 3: Modelling Framework and Choice Model Calibration

Outcomes

- Proposing a framework to solve the problem with passengers' strategic choice behaviour in high frequency transit network
- Capturing the complexities of transit user behaviour in a real-sized transit system
- Considering the fine details of spatio-temporal characteristics of a transit system
- Highlighting the significance of capturing transit users' preferences and their stochasticity in perception of transit network.
- Rectifying the correlation among the stop choices and also the correlation among the transit mode choices.

Limitations

- Due to the zone-based structure of transit fares in SEQ, travellers' sensitivities to fare could not be captured directly in the choice model calibration.

6.5.3 Chapter 4: Accessibility Estimation and Validation for the Case Study

Outcomes

- Capturing the benefits of transit diversity in perception of transit users
- Capturing the stochasticity and subjectivity of travellers in perception of transit network
- Emphasising the importance of considering the transit service characteristics in the model (e.g. number of routes, transit fare and number of transfers)
- Highlighting the importance of estimating the transit users' difficulties in travelling through the entire transit network (including "first-and-last mile" problem)
- Examining the robustness and reliability of the model in comparison with only-travel-time approaches
- Highlighting the importance of applying accurate transit accessibility measurements in the land value assessment models.

6.5.4 Chapter 5: Model Sensitivities in Policy Analysis Applications

Outcomes

- Highlighting the importance of investment in providing the diverse transit services at the mode level ("cross-nest" services)
- Exploring the value of creating direct routes (without transfer) to attractiveness points
- Clarifying the importance of providing shelter amenities in different areas instead of concentrating these services in a region

- Quantifying the importance of reducing transit fares in perception of users
- Exploring the effectiveness of creating 15-minute walkable stop catchment areas on the accessibility.

6.6 LIMITATIONS

This research used HTS data from the greater Brisbane metropolitan region (Southeast Queensland, SEQ) in Australia. Although, this data set provides fine-detail information about travellers' behaviour, it could not explain the travellers' choice behaviour at the route level. On the other word, a route which has been chosen by a transit user for travelling to destination (observed transit route) necessarily do not show his/her actual choice when he/she decided to start his/her trip from origin. As a result, the HTS dataset has a limitation to demonstrate the passengers' strategic path choice behaviour in the transit network due to inconsistencies between the observed passengers' behaviour and their actual choices.

As a suggestion for future household travel surveys, this research proposes to include some inquiries about the transit users' route preferences (before starting their trip through the transit network). By answering to these questions, the choice modeller will be able to perform more investigation about transit users' strategic choice behaviour at the route level.

It is important to note that to overcome this data limitation, the proposed choice model in this research has developed at the stop level which solved the problem with accurate prediction of path choices in the transit network.

6.7 RECOMMENDATION FOR FUTURE RESEARCH

The three most significant areas needing further research investigation are as follows:

- A closer focus on the different socio-demographic groups of people, in order to understand the differences among those groups in their behaviours and their perceptions of transit network. The outcome of this research can also help to find optimal transit polices to improve the accessibility for different groups of people and consequently, improve the social equity in the transit network.

- Adding the choice of destinations to the transit network accessibility model. By including the destination choice features, we will be able to incorporate the importance of different opportunities or the benefit-side of accessibility into the model.

- The incorporation of temporal features (e.g. day of week, time of day and weather condition) into the choice model. The results of such a model would be helpful for understanding travellers' preferences and their behaviours in different conditions such as in peak-time or during weekends.

- Although applying random utility approach helps us to capture subjectivity of travellers, measuring errors and the errors associate with missing attributes, adding more high resolution attributes can improve the result of the measurement by reducing the unobserved heterogeneity in the model. Increasing the web-based or online survey methods in the future will assist modeller to take more detailed information about the travellers' behaviour and their strategic choice into account. Consequently, this can improve the modelling prediction and its accuracy.

Bibliography

ABS. (2015a). Population Estimates by Statistical Geography (ASGS 2011), 1991 to 2013 Retrieved from Australian Bureau of Statistics, http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3218.02012-13?OpenDocument

ABS. (2015b). Statistical Geography. Retrieved from Australian Bureau of Statistics, http://www.abs.gov.au/websitedbs/D3310114.nsf/home/Geography?opendocument#from-banner=LN

Ai, P. (2005). Residential land value modelling. *International Institute for Geo-Information Science and Earth Observation, The Netherlands*.

Alam, B. M., Thompson, G. L., & Brown, J. R. (2010). Estimating Transit Accessibility with an Alternative Method. *Transportation Research Record: Journal of the Transportation Research Board, 2144*(1), 62-71.

Azar, K. T., Ferreira Jr, J., & Wiggins, L. (1994). Using GIS tools to improve transit ridership on routes serving large employment centers: The Boston South End Medical Area case study. *Computers, environment and urban systems, 18*(3), 205-231.

Banister, D. (2009). Recycling Cities–Urban Planning and Spatial Form In *keynote paper for presentation at the Velo-City 2009 Conference, Brussels* (Vol. 12).

Bekhor, S., Ben-Akiva, M. E., & Ramming, M. S. (2006). Evaluation of choice set generation algorithms for route choice models. *Annals of Operations Research, 144*(1), 235-247.

Ben-Akiva, M., & Bierlaire, M. (1999). Discrete choice methods and their applications to short term travel decisions. In *Handbook of transportation science* (pp. 5-33): Springer.

Ben-Akiva, M., & Boccara, B. (1995). Discrete choice models with latent choice sets. *International Journal of Research in Marketing, 12*(1), 9-24.

Ben-Akiva, M., & Lerman, S. R. (1979). Disaggregate travel and mobility choice models and measures of accessibility. *Behavioural travel modelling*, 654-679.

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand* (Vol. 9): MIT press.

Bertolini, L. (2005). Sustainable urban mobility, an evolutionary approach. *European Spatial Research and Policy, 12*(1), 109.

Bhat, C. (1998). Analysis of travel mode and departure time choice for urban shopping trips. *Transportation Research Part B: Methodological, 32*(6), 361-371.

Bhat, C., Carini, J. P., & Misra, R. (1999). Modeling the generation and organization of household activity stops. *Transportation Research Record: Journal of the Transportation Research Board, 1676*(1), 153-161.

Bhat, C., Govindarajan, A., & Pulugurta, V. (1998). Disaggregate attraction-end choice modeling: formulation and empirical analysis. *Transportation Research Record: Journal of the Transportation Research Board, 1645*(1), 60-68.

Bhat, C., Handy, S., Kockelman, K., Mahmassani, H., Chen, Q., & Weston, L. (2000). Urban accessibility index: literature review. *Austin: Texas Department of Transportation*.

Bierlaire, M. (2006). BIOGEME: a free package for the estimation of discrete choice models. In *Swiss Transport Research Conference*.

Bierlaire, M., & Fetiarison, M. (2009). Estimation of discrete choice models: extending biogeme. In *Swiss Transport Research Conference (STRC)*.

Black, J., & Conroy, M. (1977). Accessibility measures and the social evaluation of urban structure. *Environment and Planning A, 9*(9), 1013-1031.

Bonsall, P. W., Champernowne, A., Mason, A., & Wilson, A. (1977). Transport modelling: sensitivity analysis and policy testing. *Progress in Planning, 7*, 153-237.

Bovy, P. H. (2009). On modelling route choice sets in transportation networks: a synthesis. *Transport reviews, 29*(1), 43-68.

Bovy, P. H., Bekhor, S., & Prato, C. G. (2008). The factor of revisited path size: Alternative derivation. *Transportation Research Record: Journal of the Transportation Research Board, 2076*(1), 132-140.

Bovy, P. H., Bekhor, S., & Prato, C. G. (2009). Route sampling correction for stochastic route choice set generation. In *Transportation Research Board 88th Annual Meeting*.

Bovy, P. H., & Fiorenzo-Catalano, S. (2007). Stochastic route choice set generation: behavioral and probabilistic foundations. *Transportmetrica, 3*(3), 173-189.

Breheny, M. J. (1978). The measurement of spatial opportunity in strategic planning. *Regional Studies, 12*(4), 463-479.

Brin, S., & Page, L. (1998). The anatomy of a large-scale hypertextual Web search engine. *Computer networks and ISDN systems, 30*(1), 107-117.

Bruinsma, F., & Rietveld, P. (1998). The accessibility of European cities: theoretical framework and comparison of approaches. *Environment and Planning A, 30*(3), 499-521.

Burke, M., & Brown, A. (2007). Active Transport in Brisbane: how much is happening and what are its characteristics? In *Proceedings of State of Australian Cities National Conference. University of South Australia, Adelaide* (pp. 656-667).

Burns, L. D. (1980). Transportation, temporal, and spatial components of accessibility. *Lexington Books, Lexington/Toronto*.

Cao, X., & Hough, J. A. (2012). Hedonic Value of Transit Accessibility: An Empirical Analysis in a Small Urban Area. In *Journal of the Transportation Research Forum* (Vol. 47).

Cascetta, E. (2001). *Transportation systems engineering: theory and methods* (Vol. 49): Springer Science & Business Media.

Cascetta, E., Cartenì, A., & Montanino, M. (2013). A New Measure of Accessibility based on Perceived Opportunities. *Procedia - Social and Behavioral Sciences, 87*(0), 117-132. Retrieved from http://www.sciencedirect.com/science/article/pii/S1877042813040433.

Cascetta, E., Nuzzolo, A., Russo, F., & Vitetta, A. (1996). A modified logit route choice model overcoming path overlapping problems: specification and some calibration results for interurban networks. In *Proceedings of the 13th International Symposium on Transportation and Traffic Theory* (pp. 697-711): Pergamon Lyon, France.

Cascetta, E., & Papola, A. (2001). Random utility models with implicit availability/perception of choice alternatives for the simulation of travel demand. *Transportation Research Part C: Emerging Technologies, 9*(4), 249-263.

Cascetta, E., Russo, F., Viola, F. A., & Vitetta, A. (2002). A model of route perception in urban road networks. *Transportation Research Part B: Methodological, 36*(7), 577-592.

Cats, O. (2011). *Dynamic modelling of transit operations and passenger decisions*. Technion-Israel Institute of Technology, Faculty of Civil and Environmental Engineering.

Cats, O., Koutsopoulos, H. N., Burghout, W., & Toledo, T. (2011). Effect of real-time transit information on dynamic path choice of passengers. *Transportation Research Record: Journal of the Transportation Research Board, 2217*(1), 46-54.

Cerdá, A. (2009). Accessibility: a performance measure for land-use and transportation planning in the Montréal Metropolitan Region. *Supervised Research Project Report, School of Urban Planning McGill University*.

Cervero, R., Rood, T., & Appleyard, B. (1995). Job accessibility as a performance indicator: An analysis of trends and their social policy implications in the San Francisco Bay Area. *University of California Transportation Center*.

Chen, A., Yang, C., Kongsomsaksakul, S., & Lee, M. (2007). Network-based accessibility measures for vulnerability analysis of degradable transportation networks. *Networks and Spatial Economics, 7*(3), 241-256.

Chriqui, C., & Robillard, P. (1975). Common bus lines. *Transportation Science, 9*(2), 115-121.

Chu, C. (1989). A paired combinatorial logit model for travel demand analysis. In *Transport Policy, Management & Technology Towards 2001: Selected Proceedings of the Fifth World Conference on Transport Research* (Vol. 4).

Church, R. L., Noronha, V., Lei, T., Corrigan, W., Burbidge, S., & Marston, J. (2005). Spatial and Temporal Utility Modeling to Increase Transit Ridership.

Currie, G. (2004). Gap analysis of public transport needs: measuring spatial distribution of public transport needs and identifying gaps in the quality of public transport provision. *Transportation Research Record: Journal of the Transportation Research Board, 1895*(1), 137-146.

Currie, G. (2010). Quantifying spatial gaps in public transport supply based on social needs. *Journal of Transport Geography, 18*(1), 31-41.

Currie, G., & Stanley, J. (2008). Investigating links between social capital and public transport. *Transport Reviews, 28*(4), 529-547.

Dalvi, M. Q., & Martin, K. (1976). The measurement of accessibility: some preliminary results. *Transportation, 5*(1), 17-42.

Davidson, P. (2008). *Land Use and Public Transportation Accessibility Index (LUPTAI)Model Improvements. Final Report*. Retrieved from Queensland Transport Integrated Transport Planning

Densmore, K., & Mulley, C. (2012). Accessibility and residual land value uplift: identifying spatial variations in the accessibility impacts of a bus transitway.

Desaulniers, G., & Hickman, M. (2003). Public transit. *Transportation, handbooks in operations research and management science*, 69-127.

Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische mathematik, 1*(1), 269-271.

DNRM, D. o. N. R. a. M. (2014). *Landowner guide to statutory land valuation objections*. Retrieved from https://www.dnrm.qld.gov.au/__data/assets/pdf_file/0007/140884/site-value-objection-guide.pdf

Doi, K., Kii, M., & Nakanishi, H. (2008). An integrated evaluation method of accessibility, quality of life, and social interaction. *Environment and planning. B, Planning & design, 35*(6), 1098.

Dong, X., Ben-Akiva, M. E., Bowman, J. L., & Walker, J. L. (2006). Moving from trip-based to activity-based measures of accessibility. *Transportation Research Part A: policy and practice, 40*(2), 163-180.

Douglas, N., & Wallis, I. (2013). Predicting the Value of Public Transport In-Vehicle Time. In *Australasian Transport Research Forum, Brisbane, Australia*.

DSDIP. (2009). *South east Queensland regional plan 2009-2031*. Retrieved from

DTMR. (2010a). *Connecting SEQ 2031–An Integrated Regional Transport Plan for South East Queensland*. Retrieved from

DTMR. (2010b). Survey Procedures and Documentation-Brisbane Survey 2009. *Department of Transport and Main Roads, V2.2*.

DTMR. (2010c). Survey Procedures and Documentation-Gold Coast Survey 2009. *Department of Transport and Main Roads, v1.0*.

DTMR. (2010d). Survey Procedures and Documentation-Sunshine Coast Survey 2009. *Department of Transport and Main Roads, v1.0*.

DTMR. (2012). Public Transport Travel (Travel in south-east Queensland). *Department of Transport and Main Roads*.

Du, H., & Mulley, C. (2007). The short-term land value impacts of urban rail transit: Quantitative evidence from Sunderland, UK. *Land Use Policy, 24*(1), 223-233.

El-Geneidy, A., & Levinson, D. (2006). Access to destinations: Development of accessibility measures. 2006. *Minnesota Department of Transportation: Minnesota*, 124.

El-Geneidy, A., Tetreault, P., & Surprenant-Legault, J. (2010). Pedestrian access to transit: Identifying redundancies and gaps using a variable service area analysis. In *Transportation Research Board 89th Annual Meeting*.

Envall, P. (2007). *Accessibility Planning: a chimera?* The University of Leeds.

Flowerdew, R., & Aitkin, M. (1982). A Method of Fitting the Gravity Model Based on the Poisson Distribution *Journal of regional science, 22*(2), 191-202.

Foda, M., & Osman, A. (2010). Using GIS for measuring transit stop accessibility considering actual pedestrian road network. *Journal of Public Transportation, 13*(4).

Foda, M. A., & Osman, A. O. (2008). A GIS approach to study the bus transit network accessibility: case study: the city of Alexandria. *Journal of Arab Academy for Science, Technology & Maritime Transport, 34*(65).

Fonzone, A., & Bell, M. G. (2010). Bounded rationality in hyperpath assignment: the locally rational traveller model. *TRB 2010 Annual Meeting*.

Fonzone, A., Schmocker, J.-D., Kurauchi, F., & Hassan, S. M. (2013). Strategy Choice in Transit Networks. *Journal of the Eastern Asia Society for Transportation Studies, 10*, 796-815.

Fonzone, A., Schmoecker, J.-D., Bell, M. G., Gentile, G., Kurauchi, F., Noeckel, K., & Wilson, N. H. (2010). Do "hyper-travellers" exist?–Initial results of an international survey on public transport user behaviour.

Fonzone, A., Schmoecker, J.-D., Kurauchi, F., & Hassan, S. M. (2013). Strategy Choice in Transit Networks. *Journal of the Eastern Asia Society for Transportation Studies, 10*(0), 796-815.

Fotheringham, A., & O'Kelly, M. (Singer-songwriters). (1989). Spatial interaction models: formulations and applications. 1989. On: Kluwer Academic Publishers, Dordrecht, Boston.

Frejinger, E. (2007). Random sampling of alternatives in a route choice context. In *Proceedings of the European Transport Conference*.

Frejinger, E. (2008). *Route choice analysis: data, models, algorithms and applications*. École Polytechnique Federale de Lausanne.

Frejinger, E., Bierlaire, M., & Ben-Akiva, M. (2009). Sampling of alternatives for route choice modeling. *Transportation Research Part B: Methodological, 43*(10), 984-994.

Fu, Q., Liu, R., & Hess, S. (2012). A review on transit assignment modelling approaches to congested networks: a new perspective. *Procedia-Social and Behavioral Sciences, 54*, 1145-1155.

Gan, A., Kaiyu Liu, and Ike Ubaka. (2005). Florida Transit Geographic Information System (FTGIS). *Conference on GIS in Transit, National Center for Transit Research (NCTR).*

GCCC, G. C. C. (2015). City of GoldCoast. Retrieved from http://www.goldcoast.qld.gov.au/thegoldcoast/default.html.

Geertman, S. C., & Ritsema Van Eck, J. R. (1995). GIS and models of accessibility potential: an application in planning. *International journal of geographical information systems, 9*(1), 67-80.

Gentile, G., Nguyen, S., & Pallottino, S. (2005). Route choice on transit networks with online information at stops. *Transportation science, 39*(3), 289-297.

Geurs, K. T., & Ritsema van Eck, J. (2001). Accessibility measures: review and applications. Evaluation of accessibility impacts of land-use transportation scenarios, and related social and economic impact.

Geurs, K. T., & Van Eck, J. R. (2003). Evaluation of accessibility impacts of land-use scenarios: the implications of job competition, land-use, and infrastructure developments for the Netherlands. *Environment and Planning B, 30*(1), 69-88.

Geurs, K. T., & Van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport geography, 12*(2), 127-140.

Geurs, K. T., van Wee, B., & Rietveld, P. (2006). Accessibility appraisal of integrated land-use-transport strategies: methodology and case study for the Netherlands Randstad area. *Environment and Planning B: Planning and Design, 33*(5), 639-660.

Gilbert, R., & Tanguay, H. (2000). Sustainable transportation performance indicators project. *Brief review of some relevant worldwide activity and development of an initial long list of indicators, The Centre for Sustainable Transportation, Toronto, Ontario, Canada*.

Giuliano, G., Gordon, P., Pan, Q., & Park, J. (2010). Accessibility and residential land values: some tests with new measures. *Urban studies, 47*(14), 3103-3130.

GoogleDevelopers. (2012). What is GTFS. Retrieved from https://developers.google.com/transit/gtfs.

GoogleMaps (Cartographer). (2015). Street Map. Retrieved from https://www.google.com.au/maps/place/Cannon+Hill/@-27.4865909,153.0476442,13z/data=!4m2!3m1!1s0x6b915942d7131241:0x1d02a35bea33b770?hl=en

Greene, D. L., & Wegener, M. (1997). Sustainable transport. *Journal of Transport Geography, 5*(3), 177-190.

Gulhan, G., Ceylan, H., Özuysal, M., & Ceylan, H. (2013). Impact of utility-based accessibility measures on urban public transportation planning: A case study of Denizli, Turkey. *Cities, 32*, 102-112.

Guy, C. M. (1983). The assessment of access to local shopping opportunities: a comparison of accessibility measures. *Environment and Planning B: Planning and Design, 10*(2), 219-238.

Hadas, Y. (2013). Assessing public transport systems connectivity based on Google Transit data. *Journal of Transport Geography, 33*, 105-116.

Hägerstraand, T. (1970). What about people in regional science? *Papers in regional science, 24*(1), 7-24.

Handy, S. L. (1992). Regional versus local accessibility: neo-traditional development and its implications for non-work travel. *Built Environment (1978-)*, 253-267.

Handy, S. L. (2002). Accessibility-vs. mobility-enhancing strategies for addressing automobile dependence in the US. *Institute of Transportation Studies*.

Handy, S. L., & Clifton, K. J. (2001). Evaluating neighborhood accessibility: Possibilities and practicalities. *Journal of Transportation and Statistics, 4*(2/3), 67-78.

Handy, S. L., & Niemeier, D. A. (1997). Measuring accessibility: an exploration of issues and alternatives. *Environment and planning A, 29*(7), 1175-1194.

Hansen, W. G. (1959). How accessibility shapes land use. *Journal of the American Institute of Planners, 25*(2), 73-76.

Hanson, S. (1995). Getting there: urban transportation in context. *Geography of urban transportation*.

Hess, D. B., & Almeida, T. M. (2007). Impact of proximity to light rail rapid transit on station-area property values in Buffalo, New York. *Urban Studies, 44*(5-6), 1041-1068.

Hickman, M. D. (1996). Assessing the impact of real-time information on transit passenger behavior. *Transportation Research Part A, 30*(1), 66-67.

Hickman, M. D. (2001). An analytic stochastic model for the transit vehicle holding problem. *Transportation Science, 35*(3), 215-237.

Hickman, M. D., & Bernstein, D. H. (1997). Transit service and path choice models in stochastic and time-dependent networks. *Transportation Science, 31*(2), 129-146.

Hickman, M. D., & Wilson, N. H. (1995). Passenger travel time and path choice implications of real-time transit information. *Transportation Research Part C: Emerging Technologies, 3*(4), 211-226.

Hillman, R., & Pool, G. (1997). GIS-based innovations for modelling public transport accessibility. *Traffic engineering & control, 38*(10), 554-559.

Hoogendoorn-Lanser, S., van Nes, R., & Bovy, P. (2005). Path size modeling in multimodal route choice analysis. *Transportation Research Record: Journal of the Transportation Research Board, 1921*(1), 27-34.

Horning, J., El-Geneidy, A. M., & Krizek, K. (2008). Access to destinations: Parcel level land use data acquisition and analysis for measuring non-auto accessibility.

Huisman, O. (Singer-songwriter). (2005). A Conceptual and Operational Definition of Accessibility: Report for Objective 3 Milestone 2− Reduced CO2 from Sustainable Household Travel. On: Centre for Social and Health Outcomes Research and Evaluation (SHORE) and Te Ropu Whariki, Massey University, Auckland.

Iacono, M., Krizek, K., & El-Geneidy, A. M. (2008). Access to destinations: how close is close enough? Estimating accurate distance decay functions for multiple modes and different purposes.

Iacono, M., Krizek, K. J., & El-Geneidy, A. (2010). Measuring non-motorized accessibility: issues, alternatives, and execution. *Journal of Transport Geography, 18*(1), 133-140.

Iacono, M., & Levinson, D. (2011a). *Accessibility dynamics and location premia: Do land values follow accessibility changes?* Retrieved from http://nexus.umn.edu

Iacono, M., & Levinson, D. (2011b). Location, regional accessibility, and price effects. *Transportation Research Record: Journal of the Transportation Research Board, 2245*(1), 87-94.

Ikhrata, H., & Michell, P. (1997). Technical report of southern California association of governments' transportation performance indicators. *Transportation Research Record: Journal of the Transportation Research Board, 1606*(1), 103-114.

Ingram, D. R. (1971). The concept of accessibility: a search for an operational form. *Regional studies, 5*(2), 101-107.

Jones, S. (1981). Accessibility measures: a literature review. *TRRL Report 967*.

Kerrigan, M., & Bull, D. (1992). Measuring accessibility-a public transport accessibility index. In *Environmental Issues. Proceeding of Seminars B Held at the PTRC European Transport, Highways and Planning 20th Summer Annual Meeting,(September 14-18 1992), UMIST. Volume P354*.

Khani, A. (2013). Models and solution algorithms for transit and intermodal passenger assignment (Development of FAST-TrIPs Model).

Khani, A., Hickman, M., & Noh, H. (2014). Trip-Based Path Algorithms Using the Transit Network Hierarchy. *Networks and Spatial Economics*, 1-19.

Khani, A., Lee, S., Hickman, M., Noh, H., & Nassir, N. (2012). Intermodal path algorithm for time-dependent auto network and scheduled transit service. *Transportation Research Record: Journal of the Transportation Research Board, 2284*(1), 40-46.

Kim, H.-M., & Kwan, M.-P. (2003). Space-time accessibility measures: A geocomputational algorithm with a focus on the feasible opportunity set and possible activity duration. *Journal of Geographical Systems, 5*(1), 71-91.

Knox, P. L. (1978). The intraurban ecology of primary medical care: patterns of accessibility and their policy implications. *Environment and Planning A, 10*(4), 415-435.

Koenig, J.-G. (1980). Indicators of urban accessibility: theory and application. *Transportation, 9*(2), 145-172.

Koppelman, F. S., & Bhat, C. (2006). A self instructing course in mode choice modeling: multinomial and nested logit models. *US Department of Transportation, Federal Transit Administration, 31*.

Koppelman, F. S., & Wen, C.-H. (2000). The Paired Combinatorial Logit Model: Properties, Estimation and Application. *Transportation Research: Part B: Methodological, 34*(2), 75-89. Retrieved from EconLit.

Kremelberg, D. (2010). *Practical Statistics: A Quick and Easy Guide to IBM (R) SPSS (R) Statistics, Stata, and Other Statistical Software*: SAGE Publications.

Kurauchi, F., Schmöcker, J.-D., Fonzone, A., Hemdan, S. M. H., Shimamoto, H., & Bell, M. G. (2012). Estimating weights of times and transfers for hyperpath travelers. *Transportation Research Record: Journal of the Transportation Research Board, 2284*(1), 89-99.

Kurauchi, F., Schmöcker, J.-D., Shimamoto, H., & Hassan, S. M. (2014). Variability of commuters' bus line choice: an analysis of oyster card data. *Public Transport, 6*(1-2), 21-34.

Kwan, M.-P., Murray, A. T., O'Kelly, M. E., & Tiefelsdorf, M. (2003). Recent advances in accessibility research: Representation, methodology and applications. *Journal of Geographical Systems, 5*(1), 129-138.

Kwan, M. P. (1998). Space-time and integral measures of individual accessibility: a comparative analysis using a point-based framework. *Geographical analysis, 30*(3), 191-216.

Lam, S.-H., & Xie, F. (2002). Transit path-choice models that use revealed preference and stated preference data. *Transportation Research Record: Journal of the Transportation Research Board, 1799*(1), 58-65.

Lee, B. H.-Y. (2005). Parcel-level measure of public transit accessibility to destinations. *Elsevier*.

Lee, B. H.-Y. (2009). *Accessibility and location choice: Innovations in measurement and modeling*: University of Washington.

Leech, N. L., Barrett, K. C., & Morgan, G. A. (2012). *IBM SPSS for intermediate statistics: Use and interpretation*: Routledge.

Lei, T., & Church, R. (2010). Mapping transit-based access: integrating GIS, routes and schedules. *International Journal of Geographical Information Science, 24*(2), 283-304.

Lei, T. L., Chen, Y., & Goulias, K. G. (2012). Opportunity-Based Dynamic Transit Accessibility in Southern California. *Transportation Research Record: Journal of the Transportation Research Board, 2276*(1), 26-37.

Lenntorp, B. (1977). Paths in space-time environments: A time-geographic study of movement possibilities of individuals. *Environment and Planning A, 9*(8), 961-972.

Leonardi, G. (1978). Optimum facility location by accessibility maximizing. *Environment and Planning A, 10*(11), 1287-1305.

Limentani, G. B., Ringo, M. C., Ye, F., Bergquist, M. L., & MCSorley, E. O. (2005). Beyond the t-test: statistical equivalence testing. *Analytical chemistry, 77*(11), 221 A-226 A.

Litman, T. A. (2003). Economic value of walkability. *Transportation Research Record: Journal of the Transportation Research Board, 1828*(1), 3-11.

Liu, S., & Zhu, X. (2004). An integrated GIS approach to accessibility analysis. *Transactions in GIS, 8*(1), 45-62.

Liu, Y., Bunker, J., & Ferreira, L. (2010). Transit Users' Route-Choice Modelling in Transit Assignment: A Review. *Transport Reviews, 30*(6), 753-769.

Lo, H. K., Tang, S., & Wang, D. Z. W. (2008). Managing the Accessibility on Mass Public Transit: the Case of Hong Kong. *2008, 1*(2). Retrieved from https://www.jtlu.org/index.php/jtlu/article/view/85. doi:10.5198/jtlu.v1i2.85

Lyborg, J. (2000). Towards accessibility planning by means of GIS A case study on the access to potential job opportunities by three transport modes. *Master's Thesis in Environmental Science*.

Makri, M.-C., & Folkesson, C. (1999). Accessibility measures for analyses of land use and travelling with geographical information systems. *Department of Technology and Society, Lund Institute of Technology, Lund University & Department of Spatial Planning, University of Karlskrona/Ronneby, Sweden*.

Mamun, S. A., Lownes, N. E., Osleeb, J. P., & Bertolaccini, K. (2013). A method to define public transit opportunity space. *Journal of Transport Geography, 28*, 144-154.

Marguier, P. H., & Ceder, A. (1984). Passenger waiting strategies for overlapping bus routes. *Transportation Science, 18*(3), 207-230.

Martínez, F. J., & Araya, C. A. (2000). A note on trip benefits in spatial interaction models. *Journal of Regional Science, 40*(4), 789-796.

Mavoa, S., Witten, K., McCreanor, T., & O'Sullivan, D. (2012). GIS based destination accessibility via public transit and walking in Auckland, New Zealand. *Journal of Transport Geography, 20*(1), 15-22.

Mesbah, M., & Nassir, N. (2014). *Evaluation of Cycling Accessibility for an Urban Network, Journeys*. Paper presented at Journal of LTA Academy (Singapore.

Meyer, M. D., & Miller, E. J. (2001). *Urban transportation planning: a decision-oriented approach*: McGraw-Hill, Incorporated.

Miller, H. (2007). Place-based versus people-based geographic information science. *Geography Compass, 1*(3), 503-535.

Miller, H. J. (1999). Measuring space-time accessibility benefits within transportation networks: basic theory and computational procedures. *Geographical analysis, 31*(1), 1-26.

Miller, H. J. (2005). Place-based versus people-based accessibility. *Elsevier*(ISBN 0072423323).

Miller, H. J., & Wu, Y.-H. (2000). GIS software for measuring space-time accessibility in transportation planning and analysis. *GeoInformatica, 4*(2), 141-159.

Moniruzzaman, M., & Páez, A. (2012). Accessibility to transit, by transit, and mode share: application of a logistic model with spatial filters. *Journal of Transport Geography, 24*, 198-205.

Moxnes, E. (2005). Policy sensitivity analysis: simple versus complex fishery models. *System Dynamics Review, 21*(2), 123-145.

Mulley, C. (2014). Accessibility and residential land value uplift: Identifying spatial variations in the accessibility impacts of a bus transitway. *Urban Studies, 51*(8), 1707-1724.

Murray, A. (2001). Strategic analysis of public transport coverage. *Socio-Economic Planning Sciences, 35*(3), 175-188.

Murray, A. T., Davis, R., Stimson, R. J., & Ferreira, L. (1998). Public Transportation Access. *Transportation Research Part D: Transport and Environment, 3*(5), 319-328. Retrieved from http://www.sciencedirect.com/science/article/pii/S1361920998000108. doi:http://dx.doi.org/10.1016/S1361-9209(98)00010-8

Nanda, A., & Yeh, J.-H. (2014). Spatio-temporal diffusion of residential land prices across Taipei regions. *SpringerPlus, 3*(1), 505.

Nassir, N., Hickman, M., Malekzadeh, A., & Irannezhad, E. (2015). Modeling Transit Access Stop Choices. In *Transportation Research Board 94th Annual Meeting*.

Nassir, N., Khani, A., Hickman, M., & Noh, H. (2012). Algorithm for intermodal optimal multidestination tour with dynamic travel times. *Transportation Research Record: Journal of the Transportation Research Board, 2283*(1), 57-66.

Nassir, N., Khani, A., Lee, S., Noh, H., & Hickman, M. (2011). Transit stop-level origin-destination estimation through use of transit schedule and automated data collection system. *Transportation Research Record: Journal of the Transportation Research Board*(2263), 140-150.

Nassir, N., Ziebarth, J., Sall, E., & Zorn, L. (2014). A Choice Set Generation Algorithm Suitable for Measuring Route Choice Accessibility. *The Transportation Research Board (TRB) 93rd Annual Meeting Conference, Washington, D.C.,*.

Nassir.N , H. M., Ma.Z. (2015). Activity detection and transfer identification for public transit fare card data. *Journal of Transportation*.

Nguyen, S., & Pallottino, S. (1988). Equilibrium traffic assignment for large scale transit networks. *European journal of operational research, 37*(2), 176-186.

Nguyen, S., Pallottino, S., & Gendreau, M. (1998). Implicit enumeration of hyperpaths in a logit model for transit networks. *Transportation Science, 32*(1), 54-64.

Nurlaela, S., & Pamungkas, A. (2014). Assessing the Impact of Accessibility Improvement on Property Value Capitalization Post Perth–Mandurah Railway Opening. *Procedia-Social and Behavioral Sciences, 135*, 96-105.

O'Sullivan, D., Morrison, A., & Shearer, J. (2000). Using desktop GIS for the investigation of accessibility by public transport: an isochrone approach. *International Journal of Geographical Information Science, 14*(1), 85-104.

Pandian, P., & Kavitha, K. (2012). Sensitivity Analysis in Solid Transportation Problems. *Applied Mathematical Sciences, 6*(136), 6787-6796.

Pannell, D. J. (1997). Sensitivity analysis: strategies, methods, concepts, examples. *Agric Econ, 16*, 139-152.

Pirie, G. H. (1979). Measuring accessibility: a review and proposal. *Environment and Planning A, 11*(3), 299-312.

Pitot, M., Yigitcanlar, T., Sipe, N., & Evans, R. (2006). Land Use & Public Transport Accessibility Index (LUPTAI) tool: the development and pilot application of

LUPTAI for the Gold Coast. In *ATRF06 Forum Papers (CD-ROM and online)*: Planning and Transport Research Centre (PATREC).

Polzin, S. E., Pendyala, R. M., & Navari, S. (2002). Development of time-of-day-based transit accessibility analysis tool. *Transportation Research Record: Journal of the Transportation Research Board, 1799*(1), 35-41.

Pooler, J. (1987). Measuring geographical accessibility: a review of current approaches and problems in the use of population potentials. *Geoforum, 18*(3), 269-289.

Prashker, J. N., & Bekhor, S. (1998). Investigation of stochastic network loading procedures. *Transportation Research Record: Journal of the Transportation Research Board, 1645*(1), 94-102.

Prato, C. G. (2009). Route choice modeling: past, present and future research directions. *Journal of Choice Modelling, 2*(1), 65-100.

Prato, C. G., & Bekhor, S. (2007). Modeling route choice behavior: How relevant is the composition of choice set? *Transportation Research Record: Journal of the Transportation Research Board, 2003*(1), 64-73.

Ramming, M. S. (2002). *Network knowledge and route choice* Thesis (Ph. D.). Massachusetts Institute of Technology. Retrieved from http://hdl.handle.net/1721.1/49797

Rastogi, R., & Rao, K. K. (2002). Survey design for studying transit access behavior in Mumbai City, India. *Journal of transportation engineering, 128*(1), 68-79.

Rastogi, R., & Rao, K. K. (2003). Defining transit accessibility with environmental inputs. *Transportation Research Part D: Transport and Environment, 8*(5), 383-396.

Roth, M. (2010). How Google and Portland's TriMet Set the Standard for Open Transit Data. Retrieved from http://sf.streetsblog.org/2010/01/05/how-google-and-portlands-trimet-set-the-standard-for-open-transit-data/.

RP-Data. (2014). My RP Data. Retrieved from http://www.myrp.com.au/.

Salonen, M., & Toivonen, T. (2013). Modelling travel time in urban networks: comparable measures for private car and public transport. *Journal of Transport Geography, 31*, 143-153.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., . . . Tarantola, S. (2008). *Global sensitivity analysis: the primer*: John Wiley & Sons.

Sandhu, J., & Chandrasekhar, T. (Singer-songwriters). (2006). ArcGIS network analyst tutorial. On: ESRI.

Scheurer, J., & Curtis, C. (2007). Accessibility Measures: Overview and Practical Applications. *Department of Urban and Regional Planning, Curtin University*, 52.

Schmöcker, J.-D., Shimamoto, H., & Kurauchi, F. (2013). Generation and calibration of transit hyperpaths. *Procedia-Social and Behavioral Sciences, 80*, 211-230.

Sen, A., & Matuszewski, Z. (1991). Properties of Maximum Likelihood Estimates of Gravity Model Parameters. *Journal of Regional Science, 31*(4), 469-486.

Sheffi, Y., & Powell, W. B. (1982). An algorithm for the equilibrium assignment problem with random link times. *Networks, 12*(2), 191-207.

Shen, Q. (1998). Location characteristics of inner-city neighborhoods and employment accessibility of low-wage workers. *Environment and planning B: Planning and Design, 25*(3), 345-365.

Spiess, H., & Florian, M. (1989). Optimal strategies: a new assignment model for transit networks. *Transportation Research Part B: Methodological, 23*(2), 83-102.

Telgen, M. (2010). Realistic route choice modeling. *Master's Thesis* Retrieved from University of Twente, The Netherlands.

Train, K. E. (1998). Recreation demand models with taste differences over people. *Land economics*, 230-239.

Train, K. E. (2009). *Discrete choice methods with simulation*: Cambridge university press.

Translink. (2014a). Fares Restructure. Retrieved from http://translink.com.au/farerestructure.php.

Translink. (2014b). Springfield line Schedule. Retrieved from http://jp.translink.com.au/travel-information/network-information/trains/T/springfield-line.

Tribby, C. P., & Zandbergen, P. A. (2012). High-resolution spatio-temporal modeling of public transit accessibility. *Applied Geography, 34*(0), 345-355. doi:http://dx.doi.org/10.1016/j.apgeog.2011.12.008

Tsai, C.-H. P., Mulley, C., & Clifton, G. (2012). The spatial interactions between public transport demand and land use characteristics in the Sydney Greater Metropolitan Area. *Road & Transport Research: A Journal of Australian and New Zealand Research and Practice, 21*(4), 62.

Van der Gun, J. (2013). *A Flexible Approach towards Public Transport Modelling in Travel Demand Models*. Master’s Thesis). Delft University of Technology, The Netherlands.

Van Wee, B., Hagoort, M., & Annema, J. A. (2001). Accessibility measures with competition. *Journal of Transport Geography, 9*(3), 199-208.

Wachs, M., & Kumagai, T. G. (1973). Physical accessibility as a social indicator. *Socio-Economic Planning Sciences, 7*(5), 437-456.

WalkScore. (2015). Transit Score Methodology. Retrieved from http://www.walkscore.com/transit-score-methodology.shtml.

Wang, D., Brown, G., & Mateo-Babiano, D. (2013). Beyond proximity: an integrated model of accessibility for public parks. *Asian Journal of Social Sciences & Humanities, 2*(3), 486-498.

Weber, J., & Kwan, M. P. (2002). Bringing time back in: A study on the influence of travel time variations and facility opening hours on individual accessibility. *The professional geographer, 54*(2), 226-240.

Wegener, M. (1998). Applied models of urban land use, transport and environment: state of the art and future developments. In *Network infrastructure and the urban environment* (pp. 245-267): Springer.

Weibull, J. W. (1976). An axiomatic approach to the measurement of accessibility. *Regional science and urban economics, 6*(4), 357-379.

Weibull, J. W. (1980). On the numerical measurement of accessibility. *Environment and Planning A, 12*(1), 53-67.

Wilson, A. G. (1970). *Entropy in urban and regional modelling*: Pion Ltd.

Wilson, A. G. (1971). A family of spatial interaction models, and associated developments. *Environment and Planning, 3*(1), 1-32.

Wu, B. M., & Hine, J. P. (2003). A PTAL approach to measuring changes in bus service accessibility. *Transport Policy, 10*(4), 307-320.

Yai, T., Iwakura, S., & Morichi, S. (1997). Multinomial probit with structured covariance for route choice behavior. *Transportation Research Part B: Methodological, 31*(3), 195-207.

Yigitcanlar, T., Sipe, N., Evans, R., & Pitot, M. (2007). A GIS-based land use and public transport accessibility indexing model. *Australian Planner, 44*(3), 30-37.

Zhu, X., & Liu, S. (2004). Analysis of the impact of the MRT system on accessibility in Singapore using an integrated GIS tool. *Journal of Transport Geography, 12*(2), 89-101.

Appendices

Appendix A: BIOGEME Outputs

Biogeme 2.2 (MNL Model)

Michel Bierlaire, EPFL

This file has automatically been generated.

10/13/15 19:00:14

Test MNL logit for a transit stopchoice:

Model:	Multinomial Logit
Number of estimated parameters:	5
Number of observations:	990
Number of individuals:	990
Null log-likelihood:	-2364.719
Init log-likelihood:	-2091.518
Final log-likelihood:	-1788.026
Likelihood ratio test:	1153.385
Rho-square:	0.244
Adjusted rho-square:	0.242
Final gradient norm:	+6.911e-006
Diagnostic:	Convergence reached
Run time:	00:00
Variance-covariance:	from analytical hessian
Sample file:	HTS 80.dat

Utility parameters

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
B_AccTime	-0.211	0.00929	-22.71	0.00		0.0106	-19.97	0.00	
B_FastestTTFromStop	-0.0394	0.00562	-7.01	0.00		0.00810	-4.86	0.00	
B_MinTransfers	-1.10	0.0770	-14.24	0.00		0.0914	-11.99	0.00	
B_NumofRoutes	0.102	0.0146	6.99	0.00		0.0171	5.96	0.00	
B_Shelter	0.703	0.0830	8.48	0.00		0.0846	8.31	0.00	

Biogeme 2.2 (Model M0)

Michel Bierlaire, EPFL

This file has automatically been generated.

10/29/14 13:02:53

Test NL logit for a transit stopchoice:

Model:	Nested Logit
Number of estimated parameters:	7
Number of observations:	990
Number of individuals:	990
Null log-likelihood:	-2364.719
Init log-likelihood:	-2091.518
Final log-likelihood:	-1665.042
Likelihood ratio test:	1399.354
Rho-square:	0.296
Adjusted rho-square:	0.293
Final gradient norm:	+1.064e-006
Diagnostic:	Convergence reached
Run time:	00:12
Variance-covariance:	from finite difference hessian
Sample file:	HTS 80.dat

Utility parameters

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
B_AccTime	-0.0518	0.00911	-5.69	0.00		0.00954	-5.43	0.00	
B_FastestTTFromStop	-0.00712	0.00187	-3.81	0.00		0.00242	-2.94	0.00	
B_MinTransfers	-0.213	0.0433	-4.93	0.00		0.0492	-4.33	0.00	
B_NumofRoutes	0.0206	0.00534	3.86	0.00		0.00552	3.74	0.00	
B_Shelter	0.0466	0.0242	1.93	0.05	*	0.0252	1.85	0.06	*

Model parameters

Name	Value	Std err	t-test 0	p-value	t-test 1	p-value		Robust Std err	Robust t-test 0	p-value	Robust t-test 1	p-value	
modeBusFerry	4.60	0.782	5.89	0.00	4.61	0.00		0.783	5.88	0.00	4.60	0.00	
modeTrain	4.79	1.22	3.91	0.00	3.09	0.00		1.41	3.40	0.00	2.69	0.01	

Biogeme 2.2 (Model M1)

Michel Bierlaire, EPFL

This file has automatically been generated.

10/29/14 13:16:28

Test NL logit for a transit stopchoice:

Model:	Nested Logit
Number of estimated parameters:	8
Number of observations:	990
Number of individuals:	990
Null log-likelihood:	-2364.719
Init log-likelihood:	-2064.649
Final log-likelihood:	-1662.327
Likelihood ratio test:	1404.785
Rho-square:	0.297
Adjusted rho-square:	0.294
Final gradient norm:	+7.218e-005
Diagnostic:	No further significant progress possible
Run time:	00:14
Variance-covariance:	from finite difference hessian
Sample file:	HTS 80.dat

Utility parameters

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
B_AccTime	-0.0574	0.0101	-5.70	0.00		0.0110	-5.21	0.00	
B_CfC1	0.0538	0.0269	-2.00	0.05		0.0295	-1.82	0.07	*
B_FastestTTFromStop	-0.00816	0.00212	-3.86	0.00		0.00278	-2.94	0.00	
B_MinTransfers	-0.253	0.0525	-4.82	0.00		0.0630	-4.01	0.00	
B_NumofRoutes	0.0211	0.00566	3.72	0.00		0.00594	3.55	0.00	
B_Shelter	0.0566	0.0278	2.03	0.04		0.0301	1.88	0.06	*

Model parameters

Name	Value	Std err	t-test 0	p-value	t-test 1	p-value		Robust Std err	Robust t-test 0	p-value	Robust t-test 1	p-value	
modeBusFerry	4.12	0.702	5.87	0.00	4.45	0.00		0.743	5.54	0.00	4.20	0.00	
modeTrain	4.15	1.10	3.78	0.00	2.87	0.00		1.32	3.15	0.00	2.39	0.02	

Biogeme 2.2 (Model M2)

Michel Bierlaire, EPFL

This file has automatically been generated.

10/29/14 13:31:46

Test NL logit for a transit stopchoice:

Model:	Nested Logit
Number of estimated parameters:	8
Number of observations:	990
Number of individuals:	990
Null log-likelihood:	-2364.719
Init log-likelihood:	-2068.646
Final log-likelihood:	-1662.733
Likelihood ratio test:	1403.972
Rho-square:	0.297
Adjusted rho-square:	0.293
Final gradient norm:	+1.457e-005
Diagnostic:	No further significant progress possible
Run time:	00:14
Variance-covariance:	from finite difference hessian
Sample file:	HTS 80.dat

Utility parameters

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
B_AccTime	-0.0568	0.00998	-5.69	0.00		0.0109	-5.21	0.00	
B_CfC2	0.0485	0.0258	-1.88	0.06	*	0.0283	-1.71	0.09	*
B_FastestTTFromStop	-0.00806	0.00209	-3.85	0.00		0.00275	-2.93	0.00	
B_MinTransfers	-0.249	0.0517	-4.81	0.00		0.0620	-4.02	0.00	
B_NumofRoutes	0.0210	0.00562	3.74	0.00		0.00589	3.57	0.00	
B_Shelter	0.0550	0.0274	2.01	0.04		0.0295	1.87	0.06	*

Model parameters

Name	Value	Std err	t-test 0	p-value	t-test 1	p-value		Robust Std err	Robust t-test 0	p-value	Robust t-test 1	p-value	
modeBusFerry	4.17	0.711	5.86	0.00	4.46	0.00		0.751	5.55	0.00	4.22	0.00	
modeTrain	4.21	1.11	3.79	0.00	2.89	0.00		1.33	3.17	0.00	2.42	0.02	

Biogeme 2.2 (Model M3)

Michel Bierlaire, EPFL

This file has automatically been generated.
10/29/14 11:16:11

Test NL logit for a transit stopchoice:

Model:	Nested Logit
Number of estimated parameters:	8
Number of observations:	990
Number of individuals:	990
Null log-likelihood:	-2364.719
Init log-likelihood:	-2061.611
Final log-likelihood:	-1662.107
Likelihood ratio test:	1405.224
Rho-square:	0.297
Adjusted rho-square:	0.294
Final gradient norm:	+6.864e-005
Diagnostic:	No further significant progress possible
Run time:	00:12
Variance-covariance:	from finite difference hessian
Sample file:	HTS 80.dat

Utility parameters

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
B_AccTime	-0.0577	0.0101	-5.71	0.00		0.0111	-5.21	0.00	
B_CfC3	0.0563	0.0273	-2.07	0.04		0.0299	-1.88	0.06	*
B_FastestTTFromStop	-0.00822	0.00213	-3.86	0.00		0.00279	-2.95	0.00	
B_MinTransfers	-0.255	0.0529	-4.82	0.00		0.0636	-4.01	0.00	
B_NumofRoutes	0.0211	0.00568	3.72	0.00		0.00596	3.55	0.00	
B_Shelter	0.0571	0.0280	2.04	0.04		0.0303	1.89	0.06	*

Model parameters

Name	Value	Std err	t-test 0	p-value	t-test 1	p-value		Robust Std err	Robust t-test 0	p-value	Robust t-test 1	p-value	
modeBusFerry	4.10	0.697	5.88	0.00	4.45	0.00		0.738	5.55	0.00	4.20	0.00	
modeTrain	4.12	1.09	3.77	0.00	2.86	0.00		1.31	3.15	0.00	2.38	0.02	

Appendix B: SPSS Outputs

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Land_Value

  /METHOD=ENTER Adjusted_Logsum.
```

Regression for Logsum Accessibility

[DataSet0]

Descriptive Statistics

	Mean	Std. Deviation	N
Land_Value	7.4071E2	303.31139	2597
Adjusted_Logsum	-.2578	.41423	2597

Correlations

		Land_Value	Adjusted_Logsum
Pearson Correlation	Land_Value	1.000	.354
	Adjusted_Logsum	.354	1.000
Sig. (1-tailed)	Land_Value	.	.000
	Adjusted_Logsum	.000	.
N	Land_Value	2597	2597
	Adjusted_Logsum	2597	2597

Variables Entered/Removed[b]

Model	Variables Entered	Variables Removed	Method
1	Adjusted_Logsum[a]	.	Enter

a. All requested variables entered.

b. Dependent Variable: Land_Value

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.354[a]	.125	.125	283.77156	.125	370.817	1	2595	.000

Variables Entered/Removed[b]

Model	Variables Entered	Variables Removed	Method
1	Adjusted_Logsum[a]	.	Enter

a. Predictors: (Constant), Adjusted_Logsum

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.986E7	1	2.986E7	370.817	.000[a]
	Residual	2.090E8	2595	80526.299		
	Total	2.388E8	2596			

a. Predictors: (Constant), Adjusted_Logsum

b. Dependent Variable: Land_Value

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	807.461	6.559		123.101	.000
	Adjusted_Logsum	258.911	13.445	.354	19.257	.000

a. Dependent Variable: Land_Value

```
* Curve Estimation.
TSET NEWVAR=NONE.
CURVEFIT
  /VARIABLES=Land_Value WITH Adjusted_Logsum
  /CONSTANT
  /MODEL=EXPONENTIAL
  /PRINT ANOVA

  /PLOT FIT.
```

Curve Fit for Logsum Accessibility

[DataSet0]

Model Description

Model Name		MOD_2
Dependent Variable	1	Land_Value
Equation	1	Exponential[a]
Independent Variable		Adjusted_Logsum
Constant		Included
Variable Whose Values Label Observations in Plots		Unspecified

a. The model requires all non-missing values to be positive.

Case Processing Summary

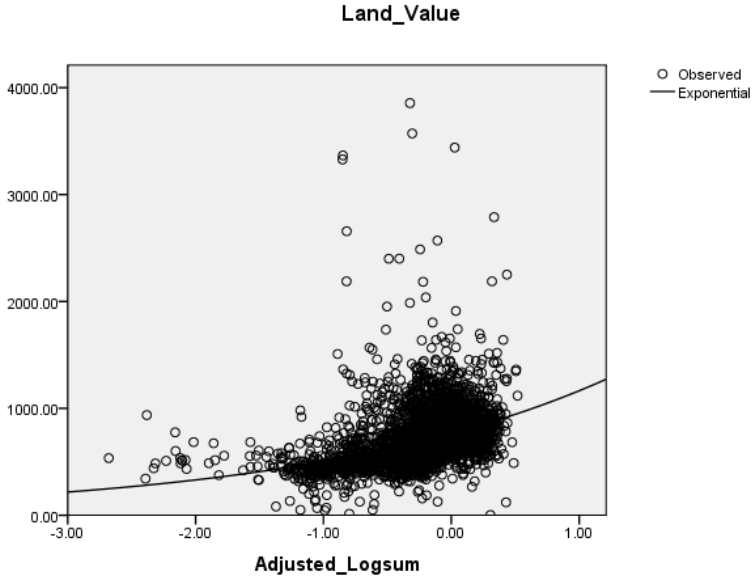
	N
Total Cases	2597
Excluded Cases[a]	0
Forecasted Cases	0
Newly Created Cases	0

a. Cases with a missing value in any variable are excluded from the analysis.

Variable Processing Summary

		Variables	
		Dependent	Independent
		Land_Value	Adjusted_Logsum
Number of Positive Values		2597	758
Number of Zeros		0	0
Number of Negative Values		0	1839
Number of Missing Values	User-Missing	0	0
	System-Missing	0	0

Land_Value
Exponential (Logsum Accessibility)



ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	78.530	1	78.530	570.449	.000
Residual	357.239	2595	.138		
Total	435.769	2596			

The independent variable is Adjusted_Logsum.

Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.425	.180	.180	.371

The independent variable is Adjusted_Logsum.

Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
Adjusted_Logsum	.420	.018	.425	23.884	.000
(Constant)	765.507	6.565		116.600	.000

The dependent variable is ln(Land_Value).

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Land_Value

  /METHOD=ENTER Fastest_Travel_Time.
```

Regression for Fastest Travel Time

[DataSet0]

Descriptive Statistics

	Mean	Std. Deviation	N
Land_Value	7.4071E2	303.31139	2597
Fastest_Travel_Time	32.4409	10.56147	2597

Correlations

		Land_Value	Fastest_Travel_Time
Pearson Correlation	Land_Value	1.000	-.330
	Fastest_Travel_Time	-.330	1.000
Sig. (1-tailed)	Land_Value	.	.000
	Fastest_Travel_Time	.000	.
N	Land_Value	2597	2597
	Fastest_Travel_Time	2597	2597

Variables Entered/Removed[b]

Model	Variables Entered	Variables Removed	Method
1	Fastest_Travel_Time[a]	.	Enter

a. All requested variables entered.

b. Dependent Variable: Land_Value

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.330[a]	.109	.109	286.33673	.109	317.916	1	2595	.000

Predictors: (Constant), Fastest_Travel_Time

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.607E7	1	2.607E7	317.916	.000[a]
	Residual	2.128E8	2595	81988.722		
	Total	2.388E8	2596			

a. Predictors: (Constant), Fastest_Travel_Time

b. Dependent Variable: Land_Value

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1048.491	18.154		57.757	.000
	Fastest_Travel_Time	-9.488	.532	-.330	-17.830	.000

a. Dependent Variable: Land_Value

```
* Curve Estimation.
TSET NEWVAR=NONE.
CURVEFIT
  /VARIABLES=Land_Value WITH Fastest_Travel_Time
  /CONSTANT
  /MODEL=EXPONENTIAL
  /PRINT ANOVA

  /PLOT FIT.
```

Curve Fit for Fastest Travel Time

Model Description

Model Name		MOD_4
Dependent Variable	1	Land_Value
Equation	1	Exponential[a]
Independent Variable		Fastest_Travel_Time
Constant		Included
Variable Whose Values Label Observations in Plots		Unspecified

a. The model requires all non-missing values to be positive.

Case Processing Summary

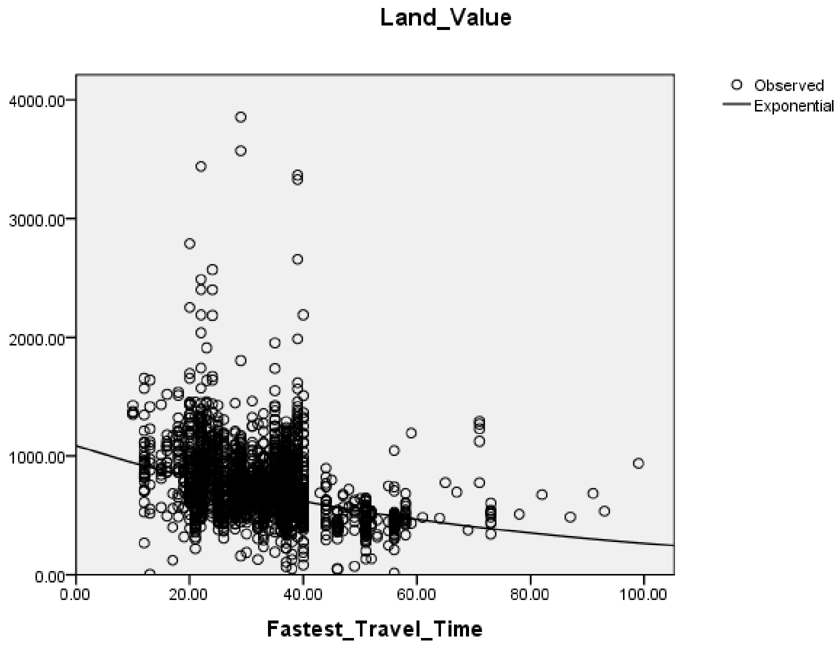
	N
Total Cases	2597
Excluded Cases[a]	0
Forecasted Cases	0
Newly Created Cases	0

a. Cases with a missing value in any variable are excluded from the analysis.

Variable Processing Summary

		Variables	
		Dependent	Independent
		Land_Value	Fastest_Travel_Time
Number of Positive Values		2597	2597
Number of Zeros		0	0
Number of Negative Values		0	0
Number of Missing Values	User-Missing	0	0
	System-Missing	0	0

Land_Value
Exponential (Fastest Travel Time)



Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.365	.133	.133	.382

The independent variable is Fastest_Travel_Time.

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	57.993	1	57.993	398.361	.000
Residual	377.776	2595	.146		
Total	435.769	2596			

The independent variable is Fastest_Travel_Time.

Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Fastest_Travel_Time	-.014	.001	-.365	-19.959	.000
(Constant)	1087.215	26.300		41.340	.000

The dependent variable is ln(Land_Value).